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Dissecting the 2007-2009 Real Estate Market Bust: Systematic Pricing Correction or Just a Housing Fad?*

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Abstract

We use a flexible Bayesian model averaging method to estimate a factor pricing model characterized by structural uncertainty and instability in macro-financial factor loadings and idiosyncratic risks. We propose such a framework to investigate key differences in the pricing mechanism that applies to residential vs. non-residential real estate investment trusts (REITs). An analysis of cross-sectional mispricings reveals no evidence of pure housing/residential real estate abnormal returns inflating between 1999 and 2007, to subsequently collapse. In fact, all REITs sectors record increasing alphas during this period, and show important differences in the dynamic evolution of risk factors exposures.

Keywords: I-CAPM, Mispricing, REIT, Model Uncertainty, Stochastic Breaks, Bayesian Econometrics

JEL codes: G12, E44, C11, C58

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1 Introduction

Most macroeconomic and policy commentaries between 2007 and 2010 have been dominated by one obsessively worrisome news item: the U.S. real estate sector was in the middle of a convulsive bust characterized by downward spiraling prices and transaction volumes. As Glaeser (2013) recently emphasized, such a bust was not the first and possibly not even the largest among those recorded in the history of the United States, but what he calls the “Great Convulsion” was sufficiently strong to produce one of the deepest recessions of the last two centuries and a full-blown financial crisis.

In this paper, we investigate whether the dominant view of the 2007-2010 real estate bust as predominantly consisting of a house price deflation phenomenon has any foundations from a rational asset pricing perspective.¹ Equivalently, we ask whether asset market transaction data are compatible with the hypothesis of any abnormal or exceptional dynamics having affected either the housing/residential or the mortgage financing sectors, differentially from other, non-residential business-related segments of the U.S. real estate market.²

We answer this question through the lens of a well established Merton (1973)-style Intertemporal CAPM (I-CAPM) setting and use advanced time series methods to understand whether the tumble in real estate prices derived from either a correction of a previous large mispricing of real estate (or parts of it), as proxied by Jensen’s alphas, or whether it was an irrationally precipitated event that is difficult to rationalize within a simple asset pricing framework. Figure 1 supports our development of formal tests of this hypothesis: the valuations of residential and mortgage real estate led other sectors between early 2007 and Summer 2008; yet, the bottom panel highlights that they also recovered before most other sectors after 2009 and appear to display dynamics that is different from business-related real estate indexes.

In methodological terms, we make two key choices; first, supported by a recent real estate finance literature (see, e.g., Cotter and Roll 2011 and Gyourko 2009) that establishes robust links between publicly traded securities and underlying real assets, we use closing market price data at monthly frequency of real estate investment trusts (REITs) to measure real estate valuations. In this respect, the use of REITs instead of property valuations is key for our purposes as our asset pricing framework requires data on liquid assets traded in a possibly frictionless market. Because REITs offer abundant, high-quality data for a variety of sectors, they give us the chance to perform tests that distinguish

among portfolios of housing-related, of mortgage, and of non-residential real estate investments. Such tests would be impossible should one use appraisal-based or repeat-sale data that are subject to upward biases and quality homogeneity issues, and generally available for houses only.

Second, we analyze the pricing of U.S. real estate assets in an encompassing no-arbitrage dynamic multi-factor framework by training a model to jointly price stocks, government bonds, corporate bonds, as well as REITs, using a set of macro-financial risk factors that are capable of pricing the cross-section of U.S. securities (see Del Negro and Otrok 2007 for a related example). As discussed by Smith and Smith (2006), to gauge the existence of mis-pricings in the real estate sector, it is fundamental to incorporate also cross-sectional data on other assets. The model emphasizes the existence of no-arbitrage conditions between real estate and other financial assets, in the tradition of Case and Shiller (1989).

Our estimation approach based on Bayesian model averaging techniques allows us to incorporate uncertainty about which combination of macroeconomic variables most effectively summarizes the properties of the pricing dynamics. Indeed, existing asset pricing theories are not explicit about which risk factors should enter as explanatory variables, and the multiplicity of potential macro-financial risk factors makes the empirical evidence difficult to interpret. Therefore, we build from existing literature and implement a Bayesian model-averaging approach in which uncertainty on the “correct” set of macro-financial risk variables can be accommodated. We assume that both the level of risk exposures and (the log of) the residual variance are time-varying and subject to stochastic discrete breaks. Finally, we relax the assumption often taken in existing empirical studies that posits that the covariance matrix of the residuals is diagonal, such that the presence of a factor structure in the residuals is not ruled out a priori.

We report a few novel findings. First, an analysis of cross-sectional mis-pricing reveals no evidence of a *pure* housing/residential real estate abnormal valuations inflating between 1999 and 2007, to subsequently burst. In fact, we obtain ex-post evidence that the *entire* real estate sector shows realized excess returns that have been higher than what would have been justified by the exposures to systematic risk factors. Additionally, and with the partial exception of lodging/resort and mortgage investments, all sector REITs describe a homogeneous dynamics over time. Between 1999 and 2007, all alphas climb up, in some cases going from a few basis point per month to as high as 1.5 percent. This was the great U.S. real estate bubble, with trading volumes, borrowing, and prices all exploding

at the same time and contradicting the occasionally reported conclusions that financial models would be able to justify the real estate valuations that were witnessed between 2004 and 2007 (see e.g., Glaeser, Gottlieb, and Gyourko 2013, Smith and Smith 2006). In this sense, the real estate fad has been pervasive. Also the claim that over-valuations in real estate would have been a debt/mortgage-fueled one is consistent with the fact that the posterior median intercept of Mortgage REITs, which was the highest in the early 2000s, sensibly dropped in 2005 anticipating an extensive correction in the pricing mechanism of real estate investments as a whole.

Second, we show that few factors carry most of the explanatory power among a large set of macro-financial variables. While market risk shows the greatest significance in explaining excess returns for equity REITs portfolios, unexpected inflation immediately ranks second to approximate the dynamic properties of the pricing kernel. Also, interest rates risk and money growth substantially affect the dynamics of excess returns on real estate investments. Except for occasional nuances, widely used macroeconomic risk factors such as aggregate credit and default spreads, liquidity, human capital, industrial production and consumption growth, do not sensibly contribute to the pricing of real estate assets.

Third, we find differences in the structure as well the dynamics of risk factor exposures across residential vs. industrial, office, and retail REITs. This means that, indeed, residential REITs, most related to housing, were “special” during our sample, and in particular during the years in which the alleged housing bubble in early 2000s built up. For instance, residential REITs are characterized by a predominantly negative exposure to the slope of the yield curve. Instead, REITs that specialize in industrial and office investments carry a neutral exposure to interest rate risk until the last part of the sample.

The paper is structured as follows. Section 2 lays out the research design and methodology. Section 3 represents the heart of the paper and contains our main empirical findings, with special emphasis on the dichotomy residential vs. business REITs. Section 4 presents a battery of economic tests used to justify the use of the proposed model as a benchmark against alternative specifications. Section 5 concludes. We leave to the appendix further details of the estimation procedure.

2 Research Design and Methodology

One crucial assumption that lies in the back of our research is that REITs may be used to proxy the valuations in the U.S. real estate market. Even though testing this connection is beyond the scope of our paper, luckily there is a well developed real estate finance literature that has examined exactly this link. While the early literature had reported mixed findings about the suitability to use REIT as a proxy for property values (see e.g., Ling and Naranjo 2003; Jirasakuldech, Campbell, and Knight 2006), most recent results are largely consistent with the claim that REITs are informative of the state of the real estate market in its various components and disaggregation (see, e.g. Clayton and MacKinnon 2003; Ghysels, Plazzi, Torous, and Valkanov 2012 and the references therein). For instance, Chiang (2009) shows that past returns on public markets can forecast returns in real, physical markets. This result is coherent with the notion that public markets are more efficient in processing information than private markets.

Finally, there is a general widespread concern that the REIT industry may be susceptible to speculative bubbles because the underlying, primitive real estate market itself is vulnerable to speculations, (see, e.g., Mikhed and Zemčík 2009, Lai and Van Order 2010, and Nneji, Brooks, and Ward 2013). Such a conjecture has been formally tested in a number of papers. Among them, Jirasakuldech et al. (2006) reject the hypothesis of rational speculative bubbles in equity REITs using a vector of macroeconomic fundamentals and a range of econometric methods, including co-integration tests. However, their data fail to include the financial crisis period and their methods fail to include ICAPM-style factor regressions, differently from our paper.

Payne and Waters (2007) use a momentum threshold auto-regressive (MTAR) model and the residuals-augmented Dickey-Fuller test to examine the possibility of periodically collapsing bubbles in the equity REIT market. They report mixed results that turn out to depend on the methods employed and on the specific equity REIT sub-sectors analyzed. On the opposite, Anderson, Brooks, and Tsolacos (2011), using a methodology based on a specific stochastic bubble process, find some evidence of periodically collapsing bubbles, especially in mortgage REIT series, a result that echoes one of our findings.

2.1 Econometric Framework

Our research design builds on a discrete-time I-CAPM framework originally developed in Merton (1973). According to the I-CAPM, if investment opportunities change over time, then assets exposures to a variety of risk factors are important determinants of average returns in addition to the market beta. In its conditional version, risk exposures are not constant but time-varying as a consequence of macroeconomic and/or asset-specific news. We follow Campbell (1996) and proxy variations in the investment opportunity set by using shocks to state variables that capture business cycle effects on beliefs and/or preferences, as characterized by a pricing kernel with time-varying properties.³

Let y_{it} be the asset returns in excess of the risk-free rate at time t , and $\mathbf{x}_t = (R_{mt}, \mathbf{u}_t)'$ the $(k+1)$ -dimensional vector of risk factors which includes the excess return on the market portfolio R_{mt} , and the k shocks to macro-financial risk factors $\mathbf{u}_t = (u_{1t}, \dots, u_{kt})'$. In its basic formulation, each asset return time series is modeled as a dynamic multi-factor linear model

$$y_{it} = \mathbf{z}_t' \boldsymbol{\beta}_{it} + \epsilon_{it}, \quad t = 1, \dots, T, \quad i = 1, \dots, n, \quad (1)$$

where the vector $\mathbf{z}_t = (1, \mathbf{x}_t)'$ includes an intercept and the risk factors, $\boldsymbol{\beta}_{it} = (\beta_{i0,t}, \beta_{im,t}, \beta_{i1,t}, \dots, \beta_{ik,t})'$ is a $(k+2)$ -vector of time-varying regression coefficients, and ϵ_{it} is such that $Cov(\mathbf{z}_{it}, \epsilon_{it}) = \mathbf{0}$. We assume that the residuals are cross-correlated, i.e. $Cov(\epsilon_{it}, \epsilon_{jt}) \neq 0$ for $i \neq j$, although they are independent over time, i.e. $Cov(\epsilon_{it}, \epsilon_{it-h}) = 0$ for $h > 0$. The model can be rewritten in a more compact form as,

$$\mathbf{y}_t = \mathbf{Z}_t' \boldsymbol{\beta}_t + \mathbf{A}^{-1} \Sigma_t \boldsymbol{\epsilon}_t, \quad t = 1, \dots, T, \quad (2)$$

with $\mathbf{y}_t = (y_{1t}, \dots, y_{nt})'$ the n -dimensional vector of assets excess returns, $\mathbf{Z}_t = \text{diag}\{\mathbf{z}_{1t}, \dots, \mathbf{z}_{nt}\}$ the block-diagonal matrix of covariates, $\boldsymbol{\beta}_t = (\boldsymbol{\beta}_{1t}', \dots, \boldsymbol{\beta}_{nt}')'$ the time-varying coefficient vector of dimension $n \times (k+2)$, $\boldsymbol{\epsilon}_t = (\epsilon_{1t}, \dots, \epsilon_{nt})'$ the vector of residuals, and $\Sigma_t = (\sigma_{1t}^2, \dots, \sigma_{nt}^2)$ a diagonal matrix for the idiosyncratic risks. Notice that Eq.(2) implies a non-diagonal time-varying covariance structure for the reduced-form disturbances $\Omega_t = \mathbf{A}^{-1} \Sigma_t (\mathbf{A}^{-1})'$ with \mathbf{A}^{-1} a lower-triangular matrix with ones on its main diagonal.⁴ A full time-varying conditional covariance structure, helps to mitigate legitimate concerns about the potential mis-specification of risk factors which can exhibit a semi-strong/strong factor structure in the residuals covariance matrix (see, e.g. Trzcinka 1986).⁵

The factor model in Eq.(2) describes a general conditional pricing framework that is known to hold under mild conditions. We specify the relationship between excess returns, factors and time-varying factor loadings and idiosyncratic risk in a state-space form (henceforth, Bayesian Model Averaging with Stochastic Break Betas and with Stochastic Break Volatility, BMA-SBB-SBV), where the time varying parameters are described by the state equations

$$\beta_{ij,t} = \beta_{ij,t-1} + \kappa_{ij,t}\eta_{ij,t} \quad i, j = 0, m, 1, \dots, k, \quad (3)$$

$$\ln(\sigma_{i,t}^2) = \ln(\sigma_{i,t-1}^2) + \kappa_{i\nu,t}\nu_{i,t} \quad i = 1, \dots, n, \quad (4)$$

with the error terms $\eta_{ij,t}, \nu_{i,t}$ independent across assets, time and risk factors, such that

$$\eta_{ij,t} \sim N(0, q_{ij}^2), \quad i, j = 0, m, 1, \dots, k,$$

$$\nu_{i,t} \sim N(0, q_{i\nu}^2), \quad i = 1, \dots, n,$$

The stochastic variation in both the level of risk exposures and (the log of) the residual variance are introduced and modeled through a change-point approach as in Ravazzolo, Paap, van Dijk, and Franses (2007), Giordani and Kohn (2008) and Bianchi, Guidolin, and Ravazzolo (2015). The latent binary random variables $\kappa_{ij,t}$ and $\kappa_{i\nu,t}$ capture the presence of stochastic changes in betas and/or idiosyncratic variance. This is formalized as;

$$\Pr[\kappa_{ij,t} = 1] = \pi_{ij}, \quad i, j = 0, m, 1, \dots, k, \quad (5)$$

$$\Pr[\kappa_{i\nu,t} = 1] = \pi_{i\nu} \quad i = 1, \dots, n \quad (6)$$

This specification is very flexible as generalizes more regular change-point processes such as Markov regime switching dynamics. More specifically, (3)-(4) capture the idea that exposures to risk factors do not necessarily change at each time t , allowing for periods in which time-invariance is imposed for some $t = \tau$ on either the betas, i.e. $\kappa_{ij,\tau} = 0$, or idiosyncratic risk, i.e. $\kappa_{i\nu,\tau} = 0$, or both $\kappa_{ij,\tau} = \kappa_{i\nu,\tau} = 0$. However, when $\kappa_{ij,\tau} = 1$ and/or $\kappa_{i\nu,\tau} = 1$, then news hits either betas or idiosyncratic variances or both, according to the random walk dynamics $\beta_{ij,\tau} = \beta_{ij,\tau-1} + \eta_{ij,\tau}$ and $\ln(\sigma_{i,\tau}^2) = \ln(\sigma_{i,\tau-1}^2) + \nu_{i,\tau}$ (or $\sigma_{i,\tau}^2 = \sigma_{i,\tau-1}^2 \exp(\nu_{i,\tau})$). When a break affects the betas and/or variances, the size of random shift is measured by q_{ij}^2 and $q_{i\nu}^2$, respectively.

We incorporate model uncertainty by introducing a set of indicator variables $\Gamma = (\gamma'_1, \dots, \gamma'_n)$, which is a block-diagonal matrix where the block corresponding to the i th equation is given by $\gamma_i = (\gamma_{i0}, \gamma_{im}, \gamma_{i1}, \dots, \gamma_{ik})'$, such that $\beta_{ij,t} = 0$ if $\gamma_{ij} = 0$, and $\beta_{ij,t} \neq 0$ if $\gamma_{ij} = 1$. We can explicitly insert these indicator variables as a multiplying element as

$$\mathbf{y}_t = Z'_t \Gamma \boldsymbol{\beta}_t + A^{-1} \Sigma_t \boldsymbol{\epsilon}_t, \quad t = 1, \dots, T, \quad (7)$$

One comment is in order. A standard problem with an I-CAPM implementation as in Eq. (2) is the difficulty with interpreting the conditional intercepts when some (or all) risk factors are not themselves traded portfolios. Unless all the factors are themselves tradable, there may be an important difference between the theoretical alpha that the model uncovers, and the actual alpha that an investor may achieve by trading assets on the basis of the multi-factor pricing model.

To avoid such a situation, we follow the literature and proceed as follows. If an economic risk factor is measured or can be deterministically converted in the form of an excess return, such as the U.S. market portfolio, credit- and default-spread variables, we use the corresponding excess returns as a mimicking portfolio; Shanken (1992) shows that under some conditions, such an approach delivers highly efficient risk premia estimates. Instead, if a risk factor is not an excess return, e.g. unemployment and money growth, we construct the corresponding $k' \leq k$ mimicking portfolios by taking the projection of the non-tradable factors onto the space of excess returns of some base assets (see e.g., Ferson and Korajczyk 1995, Lamont 2001, and Vassalou 2003).⁶

The state-space model defined by the observation equation (7) and the state equations (3)-(4) represents the most general specification we consider in this paper. However, such a framework is highly parametrized and we cannot rule out that problems related to over-parametrization could arise. Therefore, for benchmarking purposes, we also estimated models derived by imposing a number of restrictions on the dynamics of the state equation. First we consider the case with $\kappa_{iv,t} = 0 \forall i, t$, i.e. a constant idiosyncratic volatility model. We will call this model a Bayesian Model Averaging with Stochastic Break Betas model and constant idiosyncratic risks, i.e., BMA-SBB. Second, we consider a standard random walk dynamics for both the betas and idiosyncratic risks, i.e. $\kappa_{ij,t} = 1 \forall i, j, t$ and $\kappa_{iv,t} = 1 \forall i, t$. Such specification is common in some of existing literature (see, e.g. Jostova and Philipov 2005), and assumes a unit probability of breaks in the dynamics of $\beta_{ij,t}$ and $\sigma_{i,t}^2$ over time. This is fairly restrictive, and is not necessarily supported by the data, as we will document in

our empirical analysis. We call this model Bayesian Model Averaging with Random Walk Betas and with Random Walk Volatility (BMA-RWB-RWV). Trivially, the symmetric case of $\kappa_{ij,t} = \kappa_{iv,t} = 0 \forall t$ implies that $\beta_{ij,t} = \beta_{ij,t-1} = \beta_{ij}$ and $\ln(\sigma_{i,t}^2) = \ln(\sigma_{i,t-1}^2) = \ln(\sigma_i^2)$ and consists of the classical case with constant betas and idiosyncratic variances. For both the general dynamics and each of the restrictions above, we investigate the benefit of considering model uncertainty by alternatively imposing $\gamma_{ij} = 1$ for all risk factors and portfolios.

2.2 Prior Specification

Parameters and model indicators are random variables and therefore a prior is assigned to them. For the structural break probabilities, we assume Beta distributions, i.e. $\pi_{ij} \sim \text{Beta}(a_{ij}, b_{ij})$ for $i = 1, \dots, n$ and $j = 0, m, 1, \dots, k, \nu$, with a_{ij}, b_{ij} and $a_{i\nu}, b_{i\nu}$ representing the shape hyper-parameters and set according to our prior beliefs about the occurrence of structural breaks. We assume structural breaks are a priori independent across assets and factors, which allows us to greatly simplify the posterior simulation step (see Appendix A). Note that, although a priori these latent breaks are assumed to be independent across factors, portfolios, and over time, empirically we are not preventing breaks from occurring simultaneously across portfolios and/or factor exposures, as expressed by the data likelihood.

Similarly, the indicator variables γ_{ij} are assumed to be independent and distributed according to a Bernoulli distribution, i.e. $\gamma_{ij} \sim \text{Ber}(\lambda_{ij})$ for $i = 1, \dots, n$ and $j = 0, m, 1, \dots, k$, with λ_{ij} reflecting our prior beliefs about the inclusion probability of the j th risk factor in the i th portfolio. We assume the intercept is always included in the model such that $P[\gamma_{i0} = 1] = 1, \forall i$. The size of discrete changes are assumed to be distributed as an Inverse-Gamma, i.e. $q_{ij}^2 \sim \text{IG}(s_{ij}S_{ij}, S_{ij})$ for $i = 1, \dots, n$ and $j = 0, m, 1, \dots, k, \nu$. Finally, the prior distribution for the lower-triangular matrix A is a standard multivariate Normal, i.e. $A \sim N(\mu, \Omega)$. The density for the joint prior is given by the product of the priors as these are independent across assets/portfolios.

In order to mitigate the impact that flat hyper-parameters might have, an initial five-year training sample 1994:01-1998:12 is used to empirically calibrate the hyper-parameters of both time-varying parameters, change-point probabilities and corresponding break sizes.⁷ We assume a flat prior for the matrix A centered on zero with infinite variance. The testing period is 1999:01-2014:12.

2.3 Model Estimation

Although we use a conjugate prior setting, the joint posterior distribution of the latent states and the structural parameters is not available in closed form. In our framework, the latent states are represented by the time-varying factor loadings and idiosyncratic risks and their corresponding change-point indicators at each time t . The structural parameters are defined by the probability of break occurrence, the corresponding magnitude and the regression indicators which capture model uncertainty. We use a Markov Chain Monte Carlo (MCMC) approach and develop an efficient Gibbs sampling scheme which is detailed in Appendix A. Marginal posterior distributions of quantities of interest are computed as mixtures of the model-dependent marginal distributions weighted by the posterior model probabilities. Integration over the model space is performed using our MCMC scheme which, under mild regularity conditions, provides consistent estimates of the latent states and parameters. This approach enables the construction of posterior probability intervals that take into account the variability due to model uncertainty (see, e.g., Madigan and Raftery 1994).

3 Empirical Results

Our paper is based on a large panel of monthly time series sampled over the period 1994:01-2014:12. The starting date derives from the availability of monthly return series for all the sector REIT total return indexes used in this paper. Although the choice of portfolios vs. individual securities in tests of multi-factor models is a researched topic in the empirical finance literature, in our case it is the economic questions that best advise us to use portfolios of securities.

The series belong to two main categories. The first group, “Portfolio Returns”, includes stocks, bonds and real estate, organized in portfolios. The stocks are publicly traded firms listed on the NYSE, AMEX and NASDAQ and sorted according to their four-digit SIC code. Industry-based classification makes stock portfolios consistent with the investment specialization used to construct REIT portfolios. Data on government bond returns are from Ibbotson, while the 1-month T-bill and 10-year government bond yields are from FREDII at the Federal Reserve Bank of St. Louis. Data on high-yield investment grade bond returns (Baa average corporate bond yields, 10-to-20 year maturity) are from Moody’s and converted into returns using Shiller (1979)’s approximation formula. The data on sector tax-qualified REIT total returns are obtained from the North American Real Estate

Investment Trust (NAREIT) Association and consist of data on 11 portfolios formed when REITs are classified on the basis of their main focus of activity, i.e., Industrial, Office, Shopping Centers, Regional Malls, Free Standing shops, Apartments, Manufactured Homes, Healthcare, Lodging/Resorts, Self-Storage and Mortgage REITs. Apartments and Manufactured Homes represent the “Residential” real estate sector. Mortgage REITs specialize in mortgage-backed security investments. These are breakdowns common in the literature (see e.g., Payne and Waters 2007). Excess return series are computed as the difference between total returns and 1-month T-bill rates.

Second, we use a range of macroeconomic variables as standard proxies for systematic, economy-wide risk factors potentially priced in asset returns. We employ thirteen economic factors which have been previously studied in the literature: the excess return on a value-weighted market portfolio that includes all stocks traded on the NYSE, AMEX, and Nasdaq; the aggregate dividend yield on the CRSP value-weighted stock market portfolio; the unexpected inflation rate, computed as the residual of a simple ARIMA(1,1,1) model applied to the (seasonally adjusted) log CPI index; the unemployment rate; the 1-month real T-bill rate of return, computed as the difference between the 1-month T-bill nominal return and the realized CPI inflation rate; the term premium, measured as the difference between 10-year and 1-month Treasury yields; money growth, computed as changes in the money base; the credit spread, measured as the difference between Baa and Aaa Moody’s yields; the default risk premium, approximated as the difference between Baa Moody’s and 10-year Treasuries yields; the growth of (year-on-year, seasonally adjusted) industrial production; the growth of (year-on-year, seasonally adjusted) real per-capita personal consumption expenditures on non-durables and services; the traded Liquidity factor from Pastor and Stambaugh (2003); and the return on Human capital, measured as the growth rate of per-capita labor income.⁸

Figure 1 provides a visual summary of the movements of the REIT total return indexes under investigation. As a benchmark, we also plot the total return index for the value-weighted market portfolio (black solid line). To favor comparability across different sectors, all indexes are standardized to equal 100 in correspondence with the end of January 2007. This date is chosen because most of the literature (see e.g., Ait-Sahalia, Andritzky, Jobst, Nowak, and Tamirisa 2009) has dated the onset of the sub-prime crisis to early to mid-2007. To limit the number of series plotted, Industrial and Office REITs are aggregated in a “Industrial/Office” (I&O) sector, Shopping Centers, Regional Malls, Free Standing shops REITs into a “Retail” sector, and Apartments, Manufactured Homes into

a “Residential” one.

[Insert Figure 1 about here]

Two comments are in order. First, the residential sector peaks in correspondence to the end of 2006 and leads the aggregate stock market through all of 2007 and 2008. In fact, the mortgage REIT sector had already boomed between 2003 and 2005 and—consistently with most anecdotal accounts of the onset of the sub-prime crisis (e.g., Mian and Sufi 2009)—subsequently tumbled starting in late Spring 2007. Second, panel B shows that, from the Fall of 2008—approximately after the demise of Lehmann Brothers—the I&O and retail sectors started to lead (and fall at higher rate than) residential and mortgage REITs (see e.g., Greenlee 2009). Interestingly, starting in Spring 2009, all four sectors recovered somewhat, with their total return indexes approximately returning to the levels of late 2003, but the residential REIT index displays a “V-shaped” bounce-back that has no equivalent in the case of the other sectors. In fact, a simple calculation for the period January 2007 - December 2014 reveals that residential REIT is the only portfolio in Figure 1 for which average returns are positive, albeit small. In the following, we investigate the origins of these differential dynamics through the lenses of a reduced-form multi-factor asset pricing model.

3.1 Heterogeneous Mispricing in the Real Estate Sector

Figure 2 reports the marginal posterior median estimates of $\beta_{i0,t}$. In an I-CAPM implementation as in Eq. (2), $\beta_{i0,t} \neq 0$ shows evidence of a non-zero risk premium for a portfolio i with zero exposures to the K risk factors. This implies the existence of arbitrage opportunities and clashes with first principles (e.g., non-satiation). Equivalently, the time-varying alphas, $\beta_{i0,t}$ s, in our I-CAPM implementation represent abnormal returns which cannot be rationalized by the asset exposures to sources of systematic risk. The figure reports both the posterior medians (solid blue line) and the 95% credibility intervals (dashed black lines) for a set of REIT investment categories. Given our research questions, we focus our attention on REITs portfolios. Apartments and Manufactured Homes represent the “Residential” sector and the residual sub-sectors fall under the heading “Commercial” real estate sector.⁹

[Insert Figure 2 about here]

Figure 2 offers a rather stark view of a number of asset pricing trends that have involved real estate over the past decade and a half: except for Lodging/Resort, all the Jensen’s alpha related to REITs are positive and relatively large. Ex-post, we have evidence that—even in the light of a no-arbitrage multi-factor model driven by macroeconomic risks—real estate as an asset class has been persistently over-priced in the U.S., in the sense that realized excess returns have been (on average) higher than what their exposure to systematic risk would have justified between 1999 and 2014. Additionally, and with the partial exception of Lodging/Resort and Mortgage investments, all REIT portfolios describe a rather homogeneous dynamics over time: the alphas start out relatively low (in fact, near zero in the case of manufactured homes), and climb up, in some cases going from a few basis points per month in late 2000 to as high as 2.5 percent per month. This was the great U.S. real estate bubble, with trading, borrowing volumes and prices all exploding at the same time.

However, the posterior values for $\beta_{i0,t}$ for most sectors slowly declined between 2007 and 2009, settling the average levels of unexplained performances to be virtually equivalent to zero percent, when macro factors can perfectly explain average excess returns. In line with what most observers argued, there has been a dramatic drop in abnormal returns especially within the residential sector. Finally, mortgage REITs present a rather peculiar behavior over time: although the mispricing of mortgages seems to have been rather large and accurately estimated during the 2001-2005 period (when the corresponding posterior median $\beta_{mortgages,0,t}$ touched 2.5% per month), since 2005 the mortgage alphas have been declining to reach on average just a few basis points below zero between 2005 and 2008.

Figure 2 shows no evidence of a *pure* housing/residential real estate abnormal valuations—as measured by the mispricing of apartment and manufactured home-investing REITs—inflating between 2001 and 2007, to subsequently burst. All REIT sectors record a climb-up in alphas during this period. In fact, it is the alphas of the retail/distribution-investing REIT sectors that show the steepest ascent, with an increase in posterior medians between 2001 and 2007 in the range of 2 percent. Interestingly, Figure 2 shows that all equity real estate sectors are sensibly characterized by average positive, although highly volatile, mispricing at the end of our sample, possibly due to the massive interventions in the mortgage-backed securities markets by the Federal Reserve between 2009 and 2011 that partly aimed at stimulating the real estate market via reduction of borrowing costs.

In conclusion, Figure 2 tells a story that only partially matches the tale of the financial crisis often

reported by the popular press and portions of the academic literature. On the one hand, it is a fact that U.S. real estate would have been grossly and systematically over-priced between 2001 and 2007. In this sense, the real estate fad has been pervasive. On the other hand, the 2007-2008 real estate bust did not simply consist of a temporary residential real estate (housing) and mortgage-driven fad, but occurred as a result of a large-scale, widespread correction of substantial mis-pricings of the entire asset class.

3.2 Time-Varying Loadings and Posterior Inclusion Probabilities

The underlying assumption of our stochastic break dynamics (3)-(4) is that all macroeconomic news do not necessarily hit investors information set at each time t . Thus, systematic risks exposures may change at any point on time, although they do not have to be restricted to change at all points. One way to assess the plausibility of our assumption is to observe the “degree” of instability, namely the probability of having a break, for each of the betas across portfolios. Figure 3 reports the posterior median estimates of the probability of having a break in the factor loadings for each REIT, stock and bond portfolios computed from our benchmark BMA-SBB-SBV specification.

[Insert Figure 3 about here]

Bond portfolios show the highest instability in betas, with an average probability of a change point in the betas which is slightly lower than 30% across factors. The instability of the betas is rather homogeneous across macro-financial factors. While stocks show an intermediate level of instability, betas for REIT portfolios appear to be more stable over time. Indeed, the average break probability fluctuates between 10% to 15% across factors and sub-sectors. As a whole, Figure 3 shows that infrequent breaks in betas are isolated by our estimation procedure, making less parsimonious, although benchmark-worthy, dynamics such as random walks less inefficient. We formally compare the performance of our baseline specification and the random walk restriction for betas and idiosyncratic risks in Section 4.

The BMA-SBB-SBV specification allows to assess the posterior probability that a given factor enters in the dynamics of the pricing kernel. This probability can be inferred from the MCMC posterior draws as $\hat{\lambda}_{ij} = \frac{1}{G} \sum_{g=1}^G \gamma_{ij}^{(g)}$ for $i = 1, \dots, n$ and $j = m, 1, \dots, k$ with G the number of draws. In words, $\hat{\lambda}_{ij}$ represents the importance of the j th risk factor in the pricing of the i th portfolio. Figure

4 shows the estimates across REIT portfolios.

[Insert Figure 4 about here]

Few factors turn out to be crucial for the pricing of real estate. More specifically, while aggregate dividend yield, unemployment, consumption growth, aggregate credit/default risk and human capital do not seem to affect the dynamics of REIT returns, market risk, unexpected inflation, and interest rate risk appear to be sizable pricing factors. Aggregate liquidity plays a marginal role being significant for Manufactured Homes only. However, we should bear in mind that we are investigating REITs, i.e., publicly traded vehicles that may be seen as derivatives linked to actual property values. In fact, although infrastructure and real estate may represent rather illiquid investments, REITs are not. The fact that market risk plays the most prominent role is somehow unsurprising as indeed REIT are likely heavily influenced by non-housing movements in the general US equity market. This is the reason why other macroeconomic risk factors in the pricing kernel (2) enter orthogonally with respect to market risk. In that respect, the beta for, say, unexpected inflation represents the exposure of inflation risk above and beyond the effect of the aggregate stock market.¹⁰ Although to a lower extent, money growth also turns out to be relevant for REITs dynamics. A potential explanation of the effect of money supply may lie on the implications of the quantitative easing in the aftermath of the great financial crisis of 2008/2009 as it had as its main objectives to stimulate the real estate market and affect investors' perception of risk. This is consistent with a literature that has related real estate valuations to monetary policy (see e.g., Iacovello 2005; Iacovello and Neri 2010).

Based on the results of Figure 4, we report in Figures 5-7 the posterior medians for the betas on market risk, term spread and unexpected inflation. In each plot, besides the posterior medians estimated over time (solid blue line), we also show the associated 95% credibility region (dashed black lines) of the posterior density of $\beta_{ij,t}$. However, judging of the “statistical significance” of coefficients on the basis of 95% credibility intervals represents a rather stringent criterion because the Bayesian posterior density will reflect not only the uncertainty on the individual coefficient but also the overall uncertainty on the entire model (i.e., the uncertainty on structural instability of all the coefficients as well as uncertainty on the probability of inclusion of each of the factors).

[Insert Figure 5 about here]

Figure 5 shows that over our 1999-2014 sample, REIT portfolios have a market beta that follows a similar path over time, with a marked increase between 2003 and 2008; the corresponding 95% confidence regions all come to exclude zero by the end of 2004, indicating that before the collapse of the sub-prime market, none of the REITs offered hedging against aggregate market risk. This is consistent with Chen, Roll, and Ross (1986) and simple valuation principles. Intuitively, higher market returns in the equity market have a positive effect on the income of tenants and potential house buyers, increasing the probability of the rents being paid and houses being sold. Interestingly, the exposure to market risk steadily decreases in the aftermath of the great financial crisis of 2008/2009. As a result, market risk prove to be not statistically different from zero for most REIT investment category by the end of the sample. Figure 6, indicates that over the last few years, market risk might be outweighed by the riskiness implies by the regime of zero nominal interest rates occurred at the end of the sample.

[Insert Figure 6 about here]

Except occasional nuances all REIT portfolios have negative exposures to the slope of the yield curve by the end of the sample; $\beta_{i,term,t}$ tends to be large and negative with a posterior distribution tilted away from zero, especially in the case of residential REITs. This negative relationship is similar to a “flight-to-quality” effect typical of Treasury and bond portfolios, in the sense that REITs command high risk premia exactly when the risk-less yield curve is positively sloped. This is not entirely surprising. Equity REITs often hold long-term fixed leases, and they have to pay out most of their earnings to investors. Thus, REITs may be exposed to variations in the yield curve based on their inherent investment characteristics. In fact, the fixed nature of the underlying cash flows and the limited growth opportunity of their assets, makes equity REITs resemble investments in bond portfolios (see e.g. Graff 2001). As a whole, Figures 5 and 6 confirm the traditional view often discussed in the literature that posits real estate would represent a “composite” asset class that inherits mixed features (here, factor exposures) from both stocks and bonds, (see e.g., Simpson and Ramchander 2007 and references therein).

[Insert Figure 7 about here]

Figure 7 confirms another traditional property of real estate assets, namely, real estate investments provide a good hedge against inflation. All sub-sector REIT portfolios display a strong and statistically

significantly positive correlation with unexpected inflation. This is consistent with the view that upward trending inflation increases the nominal value of future cash flows from underlying properties, e.g. rents, and therefore have a positive correlation with returns on real estate assets. Possible shocks to inflation turn out to be particularly relevant towards the end of the sample, where the joint effect of lower interest rates and expected future inflation becomes more evident. A regime of low interest rates tends to push property values up and can bolster net operating income. The more net operating income generated by a property in response to inflation, the greater the likelihood that the property will also appreciate in value, even if interest rates increase in the future, generating a positive correlation between returns on real estate investments and inflation. As a whole, infrastructure and real estate tend to have non-trivial positive betas on unexpected inflation.

Figures 5-7 show that for most factors and portfolios the BMA-SBB-SBV model reveals interesting variation in betas. However, we emphasize that such time variation is not forced upon the data, in the sense that a casual look at the plots reveals that combinations of test assets and factors can be found for which the $\beta_{ij,t}$ implies little or no instability. For instance, in the bottom-center panel of Figure 6, concerning the exposure of Mortgage and Lodging/Resort to the yield spread, the plots reveal a posterior median of $\beta_{i,Term,t}$ that is almost flat during the first half of the sample. Interestingly, for most factors the REIT sectors tend to share a common dynamics in their exposures, even when their betas are characterized by different means. For instance, in Figure 5, the $\beta_{ij,t}$ s with respect to market risk all generally increase (the only partial exception is mortgage REITs), but a comparison between sectors shows that magnitudes and rate of growths are quite different.

Our modeling framework accommodates for stochastic variations in (the log of) idiosyncratic risk with unpredictable discrete shifts. This is consistent with a growing literature (see e.g., Engle, Ghysels, and Sohn 2013) that has pointed out that residual variance, σ_{it}^2 , is subject to potentially relevant and persistent shifts over time. Figure 8 plots marginal posterior medians (solid blue line) for σ_{it}^2 estimated from our BMA-SBB-SBV model, along with 95% credibility intervals (dashed black lines).

[Insert Figure 8 about here]

The financial crisis of 2008-2009 induces an increase in idiosyncratic risk, when the model had temporarily reduced its ability to price REITs. The fact that idiosyncratic is counter-cyclical was largely expected in the light of the literature (see Campbell, Lettau, Malkiel, and Xu 2001). Large spikes

are more pronounced for mortgage-, industrial- and retail-specialized (e.g. Shopping, Regional Malls) REITs.

4 Model Assessment and Alternative Specifications

The I-CAPM implementation outlined in Section 2.1 represents the most general specification we consider in this paper. However, one may argue the results might be driven by the dynamics of risk exposures, or by the presence of heteroskedasticity versus constant idiosyncratic risk, or again by the fact that the “right” set of risk factors can be precisely set ex-ante. Although our general specification does not rule out a priori any of these possibilities, it is worth to carefully investigate if our preferred specification may hurt from a pure asset pricing perspective. Therefore, the question we ask in this section, as is common in many empirical papers, concerns the optimality of the specification we used in investigating the pricing mechanism of our test portfolios.

We first compute the Bayes factors, which are the posterior odds of our BMA-SBB-SBV relative to any alternative specification. Assuming each model is equally likely ex-ante, the Bayes factor for model \mathcal{M}_1 represents the ratio of its marginal likelihood over the one implied by the competing specification \mathcal{M}_0 , i.e. $\mathcal{BF}_{10} = p(\mathbf{y}|\mathcal{M}_1) / p(\mathbf{y}|\mathcal{M}_0)$. Following Chib (1995), we compute the marginal likelihood by importance sampling, replacing the unobservable breaks and parameters in the likelihood of the data generating process (DGP) for each draw. The DGP changes for each of the specifications we used (see section 2.1 for a discussion on alternative model restrictions). Table 1 reports the Bayes factors for each specification of the dynamics in risk exposures and residual variances, with and without accommodating for model uncertainty. As a rule of thumb a Bayes factor greater than 10 represents strong evidence in favor of \mathcal{M}_1 (see Kass and Raftery 1995).

[Insert Table 1 about here]

The top panel shows that the BMA-SBB-SBV model implies the best fitting performance across the REITs test portfolios. Unsurprisingly, the SBB-SBV model ranks second outperforming both the random walk and the homoskedastic specifications. Two comments are in order. First these results indicate that fully acknowledging the instability of potentially discrete and unequally spaced shifts in the dynamics of risk exposures might effectively help explain the time-series variation in

portfolios returns. Second, as the lowest performance of the BMA-SBB and SBB specifications show, time-varying idiosyncratic risk plays a relevant role that cannot be simply derogated by latent change-point models for the betas. Interestingly, by disregarding the fact that the “correct” set of risk factors is unknown ex-ante, sensibly deteriorates the in-sample performance of the models. The log-marginal likelihood of the same specifications with a fixed set of risk factors are significantly lower than by considering model uncertainty. The superior performance of a model with latent discrete break specifications is confirmed across both bond and industry-classified equity portfolios (bottom panel), similarly to the findings in Bianchi et al. (2015) and Nardari and Scruggs (2007) with reference to alternative applications and model specifications.

Table 1 establishes the out-performance of our benchmark BMA-SBB-SBV model using an in-sample statistical metric such as the Bayes factor. Yet, one would also like to have the comfort of some economic measures. We follow Geweke and Zhou (1996) and compute the posterior average of the squared pricing errors at each time t and across test portfolios. Conditional on the intercepts and risk exposures at time t , the minimized squared average pricing error can be computed as

$$Q_t^2 = \beta'_{0t} \left(I_n - B_t (B'_t B_t)^{-1} B'_t \right) \beta_{0t} / n, \quad t = 1, \dots, T \quad (8)$$

where I_n is an n -dimensional identity matrix, $\beta_{0t} = (\beta_{10,t}, \dots, \beta_{n0,t})'$ represent the vector of Jensen’s alphas and $B_t = (\beta'_{mt}, \beta'_{1t}, \dots, \beta'_{kt})$ is the $n \times (k + 1)$ matrix of exposures to the market portfolio and additional macro risk factors for each asset. The posterior distribution of the squared average pricing errors is obtained via draws from the Gibbs sampling scheme. Table 2 reports a set of sufficient statistics of the ratios $\sqrt{Q_{t,N}^2 | \mathcal{M}_1} / \sqrt{Q_{t,N}^2 | \mathcal{M}_0}$, in which $\sqrt{Q_{t,N}^2 | \mathcal{M}_1}$ is the square-root of (8) computed from our benchmark BMA-SBB-SBV model and $\sqrt{Q_{t,N}^2 | \mathcal{M}_0}$ represent the statistics obtained from the alternative specification.

[Insert Table 2 about here]

Our model yields the lowest pricing error across the full sample period, with an expected posterior average error around 60% lower than competing specifications. Interestingly, the performance gap tends to decline in the pre-2007 period, while it increases again in the 2007-2014 sub-sample. As a whole, the model averaging specification with discrete shifts both in the betas and in idiosyncratic risk substantially outperforms all competing specifications. Finally, we follow Ferson and Harvey (1991), Ferson and Korajczyk (1995) and Karolyi and Sanders (1998) and assess the performance of

each model specification on the basis of predictable variance decomposition tests (see Appendix B for more details). In particular, we first compute the amount of predictable variation \mathcal{VR} captured by each specification starting from our general BMA-SBB-SBV model \mathcal{M}_1 . Then, we report the ratio between \mathcal{M}_1 and each competing specification \mathcal{M}_0 , i.e. $\mathcal{VR}_{\mathcal{M}_1}/\mathcal{VR}_{\mathcal{M}_0}$. Table 3 shows the results.

[Insert Table 3 about here]

Approximately 60% more of the predictable variation in excess returns is captured by the BMA-SBB-SBV model, on average across REITs and models. As far as real estate assets are concerned, these relatively high ratios especially characterize industrial and retail commercial real estate. Also, Office and Mortgage specialized REITs are characterized by a strong increase in explained predictable variation. Such performance decreases for both government and corporate bond portfolios.

5 Conclusions

This paper tells a story that only partially matches the tale of the financial crisis often reported by the popular press and portions of the academic literature. On the one hand, it is a fact that U.S. real estate would have been grossly and systematically over-priced between 2001 and 2007. Yet, there is no evidence of a pure residential real estate bubble inflating between 1999 and 2007, to subsequently burst. Except for Lodging/Resort, all REIT sectors record a climb-up in alphas during this period, without distinctions between residential vs non-residential sectors. In this sense, we show empirically that the 2007-2008 real estate bust did not simply consist of a temporary residential real estate (housing) and mortgage-driven fad, but occurred as a result of a large-scale, widespread correction of substantial mis-pricings of the entire asset class. Also, the claim that the real estate overvaluations would have been a debt/mortgage-fueled one is consistent with the fact that a drop in mortgage REITs valuations in 2005 led other sectors.

References

Aït-Sahalia, Y., J. R. Andritzky, A. A. Jobst, S. B. Nowak, and N. T. Tamirisa (2009). How to stop a herd of running bears? market response to policy initiatives during the global financial crisis. *IMF working paper* 204.

- Anderson, K., C. Brooks, and S. Tsoolas (2011). Testing for periodically collapsing rational speculative bubbles in US REITs. *Journal of Real Estate Portfolio Management* 17(3), 227–241.
- Bianchi, D., M. Guidolin, and F. Ravazzolo (2015). Macroeconomic factors strike back: A Bayesian change-point model of time-varying risk exposures and premia in the u.s. cross-section. *Journal of Business and Economic Statistics* (forthcoming).
- Campbell, J. (1996). Understanding risk and return. *Journal of Political Economy* (104), 298–345.
- Campbell, J., M. Lettau, B. Malkiel, and Y. Xu (2001). Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *Journal of Finance* 56, 1–43.
- Carter, C. and R. Kohn (1994). On Gibbs sampling for state-space models. *Biometrika* (81), 541–553.
- Case, K. and R. Shiller (1989). The efficiency of the market for single-family homes. *American Economic Review* (79), 125–137.
- Chen, N., R. Roll, and S. Ross (1986). Economic forces and the stock market. *Journal of Business* 59, 383–403.
- Chiang, K. (2009). Discovering REIT price discovery: A new data setting. *Journal of Real Estate Finance and Economics* 39, 74–91.
- Chib, S. (1995). Marginal likelihood from the Gibbs output. *Journal of the American Statistical Association* 432, 1313–1321.
- Clark, T., A. Carriero, and M. Marcellino (2016). Large vector autoregressions with stochastic volatility and flexible priors. *Working Paper*.
- Clayton, J. and G. MacKinnon (2003). The relative importance of stock, bond and real estate factors in explaining REIT returns. *Journal of Real Estate Finance and Economics* 27, 39–60.
- Cogley, T. and T. Sargent (2005). Drifts and volatilities: Monetary policies and outcomes in the post WWII US. *Review of Economic dynamics* 8(2), 262–302.
- Cotter, J. and R. Roll (2011). A comparative anatomy of REITs and residential real estate indexes: Returns, risks and distributional characteristics. *Working Paper, UCLA*.
- Del Negro, M. and C. Otrok (2007). 99 luftballons: Monetary policy and the house price boom across u.s. states. *Journal of Monetary Economics* 54(7), 1962–1985.
- Engle, R., E. Ghysels, and B. Sohn (2013). Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics* 95(3), 776–797.
- Ferson, W. and C. Harvey (1991). The variation of economic risk premiums. *Journal of Political Economy* 99, 385–415.
- Ferson, W. and R. Korajczyk (1995). Do arbitrage pricing models explain the predictability of stock returns? *Journal of Business* (68), 309–349.
- Frühwirth-Schnatter, S. (1994). Data augmentation and dynamic linear models. *Journal of Time Series Analysis* 15, 183–202.
- George, E. and R. McCulloch (1993). Variable selection via Gibbs sampling. *Journal of the American Statistical Association* (88), 881–889.
- Gerlach, R., C. Carter, and R. Kohn (2000). Efficient bayesian inference for dynamic mixture models. *Journal of the American Statistical Association* (95), 819–828.
- Geweke, J. and G. Zhou (1996). Measuring the pricing error of the arbitrage pricing theory. *Review of Financial Studies* 9, 557–587.
- Ghysels, E., A. Plazzi, W. Torous, and R. Valkanov (2012). Forecasting real estate prices. *Handbook of Economic Forecasting* 2.

- Giordani, P. and R. Kohn (2008). Efficient bayesian inference for multiple change-point and mixture innovation models. *Journal of Business and Economic Statistics* 26, 66–77.
- Glaeser, E. (2013). A nation of gamblers: Real estate speculation and american history. *American Economic Review P&P* (103), 1–42.
- Glaeser, E., J. Gottlieb, and J. Gyourko (2013). *Can Cheap Credit Explain the Housing Boom?* In “Housing and the Financial Crisis”, edited by Edward Glaeser and Todd Sinai, University of Chicago Press.
- Goyal, A. and P. Santa-Clara (2003). Idiosyncratic risk matters! *The Journal of Finance* 58(3), 975–1007.
- Goyal, A. and I. Welch (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 4(21), 1455–1508.
- Graff, R. (2001). Economic analysis suggests that REIT investment characteristics are not as advertised. *Journal of Real Estate Portfolio Management* (7), 99–124.
- Greenlee, J. (2009). Testimony on residential and commercial real estate before the subcommittee on domestic policy. *Committee on Oversight and Government Reform, U.S. House of Representatives, Atlanta, GA*.
- Gyourko, J. (2009). Understanding commercial real estate: Just how different from housing is it? *NBER working paper No. 14708*.
- Iacovello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review* 95, 739–764.
- Iacovello, M. and S. Neri (2010). Housing market spillovers: Evidence from an estimated DSGE model. *American Economic Journal: Macroeconomics* 2, 125–164.
- Jagannathan, R. and Z. Wang (1996). The conditional CAPM and the cross-section of expected returns. *The Journal of Finance* 51(1), 3–53.
- Jin, C., G. Soydemir, and A. Tidwell (2014). The us housing market and the pricing of risk: Fundamental analysis and market sentiment. *Journal of Real Estate Research*.
- Jirasakuldech, B., R. Campbell, and J. Knight (2006). Are there rational speculative bubbles in REITs? *The Journal of Real Estate Finance and Economics* 32(2), 105–127.
- Jostova, G. and A. Philipov (2005). Bayesian analysis of stochastic betas. *Journal of Financial and Quantitative Analysis* 40, 747–778.
- Karolyi, G. and A. Sanders (1998). The variation of economic risk premiums in real estate returns. *Journal of Real Estate Finance and Economics* 17, 245–262.
- Kass, R. and A. Raftery (1995). Bayes factors. *Journal of the American Statistical Association* 430, 773–795.
- Kim, S., N. Shepard, and S. Chib (1998). Stochastic volatility: likelihood inference and comparison with arch models. *Review of Economic Studies* 65, 361–393.
- Kuo, L. and B. Mallick (1998). Variable selection for regression models. *The Indian Journal of Statistics*, 65–81.
- Lai, R. and R. Van Order (2010). Momentum and house price growth in the united states: Anatomy of a bubble. *Real Estate Economics* 38(4), 753–773.
- Lamont, O. (2001). Economic tracking portfolios. *Journal of Econometrics* 105, 161–184.
- Ling, D. and A. Naranjo (2003). The dynamics of REIT capital flows and returns. *Real Estate Economics* (31), 405–434.

- Madigan, D. and A. Raftery (1994). Model selection and accounting for model uncertainty in graphical models using occam’s window. *Journal of the American Statistical Association* 89, 1535–1546.
- Merton, R. (1973). An intertemporal capital asset pricing model. *Econometrica* 41, 867–887.
- Mian, A. and A. Sufi (2009). The consequences of mortgage credit expansion: Evidence from the u.s. mortgage default crisis. *Quarterly Journal of Economics* (124), 1449–1496.
- Mikhed, V. and P. Zemčík (2009). Testing for bubbles in housing markets: A panel data approach. *The Journal of Real Estate Finance and Economics* 38(4), 366–386.
- Nardari, F. and J. Scruggs (2007). Bayesian analysis of linear factor models with latent factors, multivariate stochastic volatility, and APT pricing restrictions. *Journal of Financial and Quantitative Analysis* 42(4), 857–891.
- Nneji, O., C. Brooks, and C. Ward (2013). Intrinsic and rational speculative bubbles in the US housing market: 1960-2011. *Journal of Real Estate Research*.
- Omori, Y., S. Chib, N. Shepard, and J. Nakajima (2007). Stochastic volatility with leverage: Fast and efficient likelihood inference. *Journal of Econometrics* 140, 425–449.
- Pastor, L. and F. Stambaugh, R. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy* (111), 642–685.
- Payne, J. and G. Waters (2007). Have equity REITs experienced periodically collapsing bubbles? *The Journal of Real Estate Finance and Economics* 34(2), 207–224.
- Primiceri, G. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies* 72, 821–852.
- Ravazzolo, F., R. Paap, D. van Dijk, and P. Franses (2007). *Bayesian Model Averaging in the Presence of Structural Breaks* (Frontiers of Economics and Globalization ed.). Elsevier.
- Shanken, J. (1992). On the estimation of beta pricing models. *Review of Financial Studies* (5), 1–34.
- Shiller, R. (1979). The volatility of long-term interest rates and expectations models of the term structure. *Journal of Political Economy* 87, 1190–1219.
- Simpson, M. and a. W. J. Ramchander, S. (2007). The asymmetric response of equity REIT returns to inflation. *Journal of Real Estate Finance and Economics* 34, 513–529.
- Smith, M. and G. Smith (2006). Bubble, bubble, where is the housing bubble? *Brookings Papers on Economic Activity* (1), 1–67.
- Trzcinka, C. (1986). On the number of factors in the arbitrage pricing model. *The Journal of Finance* 41(2), 347–368.
- Vassalou, M. (2003). News related to future GDP growth as a risk factor in equity returns. *Journal of Financial Economics* (68), 47–73.

Notes

¹Our question is mainly motivated by the fact that a vast literature has pointed out that, within the real estate asset class, housing would be more prone to bubbles (see, e.g. Mikhed and Zemčík 2009, Lai and Van Order 2010, Anderson et al. 2011, Nneji et al. 2013, and Jin, Soydemir, and Tidwell 2014)

²While residential (in particular, apartment-investing) REITs represent commercial property, the key distinction in this paper is between real estate assets that are directly related to business activities (industrial buildings, offices, shopping malls, and free-standing shops) vs. residential equity REITs that invest in manufactured homes and apartments, as well as mortgage REITs that are involved with purchasing housing-related loans and mortgage-backed securities.

³It is important to specify a process for the time-series dynamics of the innovations variables $u_{j,t}$. We adopt the approach of Campbell (1996) and assume that the macroeconomic factors follow a first-order Vector Auto-Regressive (VAR) process. To ensure that betas in model (2) are fully conditional, the VAR(1) is estimated recursively at each time t . Thus, for a collection of risk factors z_t , we estimate $z_\tau = A_0 + A_1 z_{\tau-1} + u_\tau$ for $\tau = 1, \dots, t$, and $t = t_0, \dots, T$ with t_0 an initial set of observations.

⁴In equation (2) we do not allow the elements in A^{-1} to vary over time. We do so since this would imply additional $N(N \times 1)/2$ state equations. In addition, existing literature finds little variations for A , e.g. Primiceri (2005).

⁵In a separate online Appendix we report further estimates on the conditional correlation structure obtained from our benchmark model specification. On the one hand, we find evidence of a weak factor structure in idiosyncratic risk of industry-related stocks. This is indeed consistent with existing empirical evidence, see, e.g. Goyal and Santa-Clara (2003). On the other hand, there is no evidence of a strong factor structure in the conditional dependence structure of REIT excess returns, which possibly implies a correct specification of our multi-factor pricing model for the real estate asset class.

⁶The base assets consist of six equity zero net investment portfolios sorted on size and book-to-market as well as the returns spread between long-term and short term government bonds and the return spread on long-term corporate bonds minus long-term government bonds. In a separate online appendix we show that these base assets allow to capture a great deal of sample variation of the non-tradable factors.

⁷In a separate online appendix we show that posterior estimates obtained without calibrating the priors with a five-year training sample do not lead to sensibly different results. In this respect, the results are robust to the choice of the initial five years to train the priors hyper-parameters.

⁸The per-capita labor income is constructed as the difference between total personal income and dividend payments, divided by total population (from the Bureau of Economic Analysis). The growth rate then is computed by taking a 2-month moving average of per-capita labor income minus one (see Jagannathan and Wang 1996).

⁹In order to keep the graphs as much readable as possible we left aside the results for the Healthcare and Storage sectors. Indeed, except few nuances, they share the same dynamics of the other commercial sub-sectors.

¹⁰In a separate online appendix we report a set of results concerning estimates in which we consider REIT returns orthogonalized with respect to the excess returns on the market; the results are in line with the one presented although the alphas are a bit smoother.

Appendix

A The Gibbs Sampling Algorithm

Our Gibbs sampler is a combination of the Forward Filtering Backward Sampling of Carter and Kohn (1994), Omori, Chib, Shepard, and Nakajima (2007) and the efficient sampling algorithm for the random breaks proposed in Gerlach, Carter, and Kohn (2000). Let us denote the probability of a break for the i th asset as $\boldsymbol{\pi}_i = (\pi_{i0}, \pi_{im}, \pi_{i1}, \dots, \pi_{ik}, \pi_{i\nu})'$ and the corresponding size of a break as $\mathbf{q}_i^2 = (q_{i0}^2, q_{im}^2, q_{i1}^2, \dots, q_{ik}^2)'$. The vector that collects the parameters for a given asset is defined as $\theta_i = (\boldsymbol{\gamma}_i', \mathbf{q}_i^2, \boldsymbol{\pi}_i^2)'$. Furthermore, let us collect the vector of binary structural breaks as $\mathcal{K}_{i,t} = (\kappa_{i0,t}, \kappa_{im,t}, \kappa_{i1,t}, \dots, \kappa_{ik,t})'$

From an estimation point of view, having a full stochastic volatility matrix poses significant challenges as we now have to estimate additional $N(N-1)/2$ parameters. Given our cross-section is $N = 33$, this could make the computation quite cumbersome. To solve this issue we borrow insights from a recent literature addressing stochastic volatility in large dimensional vector auto-regressive models (see, e.g. Clark, Carriero, and Marcellino 2016). Let us define $\mathbf{y}_t^* = \mathbf{y}_t - A^{-1}\Sigma_t\epsilon_t$ the change of variable that makes equations now independent on each other which allows us to estimate the model equation by equation. At each iteration of the sampler we sequentially cycle through the above steps as follows:

1. Draw $\boldsymbol{\gamma}_i$ conditional on $\sigma_{i,1:T}^2, \mathcal{K}_{i,1:T}, \kappa_{i\nu,1:T}, \theta_i, \mathbf{y}_{1:t}^*$ and $\mathbf{z}_{1:t}$, for $i = 1, \dots, n$
2. Draw $\mathcal{K}_{i,1:T}$ conditional on $\sigma_{i,1:T}^2, \theta_i, \mathbf{y}_{1:t}^*$ and $\mathbf{z}_{1:t}$, for $i = 1, \dots, n$
3. Draw $\boldsymbol{\beta}_{i,1:T}$ conditional on $\sigma_{i,1:T}^2, \mathcal{K}_{i,1:T}, \theta_i, \mathbf{y}_{1:t}^*$ and $\mathbf{z}_{1:t}$, for $i = 1, \dots, n$.
4. Draw $\kappa_{i\nu,1:T}$ conditional on $\sigma_{i,1:T}^2, \theta_i, \mathbf{y}_{1:t}^*$ and $\mathbf{z}_{1:t}$, for $i = 1, \dots, n$.
5. Draw $\sigma_{i,1:T}^2$ conditional on $\boldsymbol{\beta}_{i,1:T}, \mathcal{K}_{i,1:T}, \kappa_{i\nu,1:T}, \theta_i, \mathbf{y}_{1:t}^*$ and $\mathbf{z}_{1:t}$, for $i = 1, \dots, n$.
6. Draw θ_i conditional on $\boldsymbol{\beta}_{i,1:T}, \mathcal{K}_{i,1:T}, \kappa_{i\nu,1:T}, \mathbf{y}_{1:t}^*$ and $\mathbf{z}_{1:t}$, for $i = 1, \dots, n$.
7. Draw A conditional on $(\boldsymbol{\beta}_{i,1:T}, \dots, \boldsymbol{\beta}_{n,1:T}), \mathbf{y}_{1:t}^*$ and $\mathbf{z}_{1:t}$.

Where $\mathcal{K}_{i,1:T}$ and $\kappa_{i\nu,1:T}$ represent the time-series of stochastic breaks for the betas $\boldsymbol{\beta}_{i,1:T}$ and idiosyncratic variances $\sigma_{i,1:T}^2$, respectively. We use a burn-in period of 10,000 and draw 50,000 observations storing every 5 draws to approximate the posterior of parameters and latent variables.

Step 1. Sampling the Variable Selection γ_i

We follow George and McCulloch (1993), and Kuo and Mallick (1998) to address model uncertainty while estimating the model dynamics. Conditional on the change of variable the regressor indicator for the i th asset can be sampled from the posterior density for $\gamma_{ij} = 0$ and $\gamma_{ij} = 1$ given the value of the other parameters. The full conditional posterior for the i th asset simplifies to:

$$\begin{aligned} p(\gamma_{ij} = 1 | \gamma_{i[-j]}, \beta_{i,1:T}, \mathcal{K}_{i,1:T}, \kappa_{i\nu,1:T}, \sigma_{i,1:T}^2, \theta_i, \mathbf{y}_{1:t}^*, \mathbf{z}_{1:t}) = \\ = \frac{\lambda_{ij} \prod_{t=1}^T p(y_{it}^* | \mathbf{z}_t, \beta_{it}, \sigma_{it}^2, \gamma_{i[-j]}) |_{\gamma_{ij}=1}}{(1 - \lambda_{ij}) \prod_{t=1}^T p(y_{it}^* | \mathbf{z}_t, \beta_{it}, \sigma_{it}^2, \gamma_{i[-j]}) |_{\gamma_{ij}=0} + \lambda_{ij} \prod_{t=1}^T p(y_{it}^* | \mathbf{z}_t, \beta_{it}, \sigma_{it}^2, \gamma_{i[-j]}) |_{\gamma_{ij}=1}}, \quad (\text{A.1}) \end{aligned}$$

for $j = m, 1, \dots, k$, where $\gamma_{i[-j]} = (\gamma_{i1}, \dots, \gamma_{ij-1}, \gamma_{ij+1}, \dots, \gamma_{ik})'$. We randomly choose the order in which we sample the γ_{ij} parameters. As starting value of the Gibbs sampler we consider a model which includes all k risk factors.

Step 2 and 3. Sampling $\mathcal{K}_{i,1:T}$ and the Factor Loadings $\beta_{i,1:T}$

The structural breaks in the conditional dynamics of the factor loadings for the i th asset, measured by the latent binary state $\mathcal{K}_{i,1:T}$, are drawn using the algorithm of Gerlach et al. (2000). This algorithm increases the efficiency of the sampling procedure since allows to generate $\kappa_{ij,t}$, without conditioning on the relative regression parameters $\beta_{ij,t}$. We assume that each of the κ_{ij} s breaks are independent from each other.

Posterior draws for the time-varying betas are computed using a forward filtering backward sampling as in Frühwirth-Schnatter (1994), and Carter and Kohn (1994). Both breaks and loadings are sampled conditional on γ_i .

Step 4 and 5. Sampling $\kappa_{i\nu,1:T}$ and $\sigma_{i,1:T}^2$.

Similarly to the conditional betas we draw the structural breaks for the i th asset, i.e. $\kappa_{i\nu,1:T}$, by using the Gerlach et al. (2000) algorithm. The (log of) idiosyncratic risk, i.e. $\ln \sigma_{it}^2$, is drawn using a mixture distribution as in Kim, Shepard, and Chib (1998) and Omori et al. (2007). Mechanically in each step of the Gibbs Samplers we simulate at each time t a component of the mixture. Now, given the mixture component and the break indicator we can apply the standard Kalman filter method as in step 2 and 3.

Step 6a and 6b. Sampling the Stochastic Breaks Probabilities and Sizes.

The Beta prior for the stochastic break probabilities outlined in Section 2.2. is conjugate. As a result posterior draws are updated on the basis on the filtered unobservable break indicators $\mathcal{K}_{i,1:T}$ and $\kappa_{i\nu,1:T}$. The break probabilities for the betas are conditional on a given factor being selected, i.e. $\gamma_{ij} = 1$

$$\begin{aligned}\pi_{ij}|\mathcal{K}_{i,1:T}, \gamma_i &\sim \text{Beta}\left(a_{ij} + \sum_{t=1}^T \kappa_{ij,t} \gamma_{ij}, b_{ij} + \sum_{t=1}^T (1 - \kappa_{ij,t} \gamma_{ij})\right), \quad j = 0, m, 1, \dots, k \\ \pi_{i\nu}|\kappa_{i\nu,1:T} &\sim \text{Beta}\left(a_{i\nu} + \sum_{t=1}^T \kappa_{i\nu,t}, b_{i\nu} + \sum_{t=1}^T (1 - \kappa_{i\nu,t})\right),\end{aligned}$$

Similarly, the Inverse-Gamma prior for the conditional variances of both risk exposures and volatilities is conjugate, leading to posterior updates after sampling the betas and (log) idiosyncratic variances of the following form

$$\begin{aligned}q_{ij}^2|\beta_{i,1:T}, \gamma_i &\sim IG\left(s_{ij}S_{ij} + \sum_{t=1}^T \kappa_{ij,t} (\beta_{ij,t} - \beta_{ij,t-1})^2, S_{ij} + \sum_{t=1}^T \kappa_{ij,t}\right), \quad j = 0, m, 1, \dots, k \\ q_{i\nu}^2|\sigma_{i,1:T}, \gamma_i &\sim IG\left(s_{i\nu}S_{i\nu} + \sum_{t=1}^T \kappa_{i\nu,t} (\ln \sigma_{i,t}^2 - \ln \sigma_{i,t-1}^2)^2, S_{i\nu} + \sum_{t=1}^T \kappa_{i\nu,t}\right),\end{aligned}$$

Step 7. Sampling the Matrix A

Knowledge of the factor loadings and the idiosyncratic risks implies knowledge of the model structural residuals ϵ_t which satisfy $\Sigma_t \epsilon_t = A \epsilon_t^*$ with $\epsilon_t^* = \mathbf{y}_t - Z_t' \Gamma \beta_t$ the reduced form residuals. We can interpret this as a system of equations with orthogonal residuals (see Cogley and Sargent 2005 and Clark et al. 2016 for applications on large dimensional VAR models);

$$\begin{aligned}\epsilon_{1t}^* &= \epsilon_{1t}, \\ \sigma_{2,t}^{-1/2} \epsilon_{2t}^* &= a_{21} \left(-\sigma_{2t}^{-1/2} \epsilon_{1t}^*\right) + \sigma_{2t}^{-1/2} \epsilon_{2t} \\ \sigma_{3,t}^{-1/2} \epsilon_{3t}^* &= a_{31} \left(-\sigma_{3t}^{-1/2} \epsilon_{1t}^*\right) + a_{32} \left(-\sigma_{3t}^{-1/2} \epsilon_{2t}^*\right) + \sigma_{3t}^{-1/2} \epsilon_{3t} \\ &\vdots\end{aligned}$$

The Gaussian prior specified in Section 2.3 is conjugate and posterior draws for the i th equation can be drawn from

$$A_i | \Sigma_{1:T}, \beta_{1:T} \sim N(\mu_{A_i}, \Omega_{A_i}), \quad \mu_{A_i} = \Omega_{A_i} (\Omega^{-1} \mu + R_i' r_i), \quad \Omega_{A_i} = (\Omega^{-1} + R_i' R_i),$$

with $\Sigma_{1:T}$ the time-series collection of diagonal matrices of idiosyncratic risks, $\beta_{1:T}$ the set of time-varying loadings, and R_i and r_i the right- and left-hand side variables in the above transformed regressions.

B Predictable Variance Decomposition

Equation (2) decomposes excess asset returns in a component related to risk for each asset plus a residual. In principle, a multi-factor model is as good as the implied percentage of total variation in excess returns explained by its first component. Therefore, we follow Ferson and Harvey (1991), Ferson and Korajczyk (1995) and Karolyi and Sanders (1998), and adopt the following approach. First, the excess return on each asset is regressed onto a set of instrumental variables that proxy for available information at time $t - 1$, \mathbf{D}_{t-1}

$$y_{i,t} = \varphi_{i0} + \varphi_i' \mathbf{D}_{t-1} + \xi_{i,t}, \quad (\text{A.2})$$

to compute the sample variance of the resulting fitted values,

$$\text{Var}[P(y_{it} | \mathbf{D}_{t-1})] \equiv \text{Var}[\hat{\varphi}_{i0} + \hat{\varphi}_i' \mathbf{D}_{t-1}], \quad (\text{A.3})$$

where the notation $P(y_{it} | \mathbf{D}_{t-1})$ means “linear projection” of y_{it} on a set of instruments, \mathbf{D}_{t-1} . Second, the betas are sampled from their (marginal) posterior distribution, and we compute the fitted risk compensations, $\hat{y}_t = Z_t' \hat{\Gamma} \hat{\beta}_t$. Now, for each of the asset $i = 1, \dots, n$ we regress the model-implied risk premia onto the instrumental variables,

$$\hat{y}_{i,t} = \varphi_{i0}^* + \varphi_i^{*'} \mathbf{D}_{t-1} + \xi_{i,t}^*, \quad (\text{A.4})$$

to compute the sample variance of fitted posterior risk compensations:

$$Var [P(\hat{y}_{i,t}|\mathbf{D}_{t-1})] \equiv Var [\hat{\varphi}_{i0}^* + \hat{\varphi}_i^{*\prime} \mathbf{D}_{t-1}]. \quad (\text{A.5})$$

At this point, the predictable variance in the risk premia \mathcal{VR} that is attributed to the model, relative to the total predictable variance in the excess returns, can be computed as the ratio between Eq.(A.5) and Eq.(A.3). The set of instruments includes lagged values of the earnings-to-price, the dividend-payout ratios, and lagged credit yield spread (see, Goyal and Welch 2008 for a detailed description).

Table 1: Bayes Factors

This table reports the Bayes factors computed as the ratio between the marginal likelihood of our benchmark BMA-SBB-SBV model and competing models across assets, i.e. $\mathcal{BF}_{10} = p(\mathbf{y}|\mathcal{M}_1)/p(\mathbf{y}|\mathcal{M}_0)$ with \mathcal{M}_1 , our preferred benchmark and \mathcal{M}_0 the competing specification. A Bayes factor greater than 10 represents strong evidence in favour of \mathcal{M}_1 (see Kass and Raftery 1995). The top panel reports the Bayes factor concerning the REITs classified according to the underlying investable properties as explained in section 3 in the main text (from column 2 to 13), and the Bayes factor for government and corporate bonds (from column 14 to the end). The bottom panel reports the results for the industry sorted portfolios. The log marginal likelihood used to compute the Bayes factors are obtained from the MCMC estimation output by integrating out uncertainty on the parameters, on the “right” set of risk factors, as well as the uncertainty on time-varying risk exposures and idiosyncratic risks. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors for all models.

| | REIT | | | | | | | | | | | Bond Portfolios | | | | | |
|-------------|---------------------|--------|-------|-------|--------|-------|-------|--------|-------|---------|-------|-----------------|-------|-------|-------|------------|-------|
| | Ind | Office | Shop | Malls | FreeSt | Apts | Homes | Health | Lodg | Storage | Mortg | 10-yrs | 5-yrs | 3-yrs | 1-yrs | High-Yield | |
| BMA-SBB | 126.3 | 124.9 | 125.8 | 111.3 | 132.4 | 126.1 | 120.6 | 129.9 | 129.1 | 118.0 | 119.0 | 126.1 | 102.3 | 107.5 | 140.7 | 41.10 | |
| BMA-RWB-RWV | 40.18 | 44.25 | 41.26 | 33.36 | 50.22 | 41.38 | 47.11 | 37.38 | 34.24 | 33.24 | 27.12 | 57.67 | 56.78 | 56.24 | 65.15 | 70.26 | |
| SBB | 161.1 | 169.1 | 163.4 | 151.0 | 173.4 | 160.2 | 169.1 | 153.8 | 149.3 | 147.3 | 144.8 | 182.3 | 180.7 | 185.1 | 198.2 | 205.1 | |
| RWB-RWV | 59.39 | 70.25 | 65.36 | 51.14 | 76.17 | 65.33 | 74.24 | 60.24 | 49.73 | 55.21 | 36.41 | 87.28 | 86.38 | 85.41 | 95.24 | 102.8 | |
| SBB-SBV | 26.36 | 35.25 | 31.03 | 17.28 | 40.91 | 31.24 | 39.34 | 25.47 | 17.25 | 21.31 | 5.632 | 51.39 | 50.54 | 49.42 | 59.15 | 67.23 | |
| | | | | | | | | | | | | | | | | | |
| | Industry Portfolios | | | | | | | | | | | | | | | | |
| | Food | Mines | Oil | Clths | Durbl | Chems | Cnsum | Cnstr | Steel | FabPr | Machn | Cars | Trans | Utils | Rtail | Finan | Other |
| BMA-SBB | 112.0 | 116.4 | 119.3 | 139.4 | 64.6 | 119.8 | 101.8 | 119.2 | 133.4 | 108.1 | 134.3 | 140.1 | 59.35 | 131.8 | 95.13 | 91.33 | 55.38 |
| BMA-RWB-RWV | 66.92 | 24.29 | 44.44 | 52.72 | 55.92 | 57.37 | 54.18 | 52.75 | 46.69 | 53.24 | 52.67 | 52.65 | 59.69 | 47.66 | 62.77 | 59.86 | 66.66 |
| SBB | 193.2 | 135.6 | 158.0 | 168.6 | 179.0 | 175.3 | 179.6 | 169.2 | 169.8 | 176.8 | 179.1 | 174.7 | 183.0 | 170.0 | 184.6 | 185.3 | 194.5 |
| RWB-RWV | 98.33 | 37.69 | 68.55 | 77.40 | 85.63 | 87.62 | 85.76 | 80.41 | 70.63 | 82.66 | 82.06 | 79.40 | 90.34 | 75.36 | 92.46 | 90.41 | 100.9 |
| SBB-SBV | 61.69 | 4.635 | 33.61 | 43.61 | 50.32 | 51.31 | 49.53 | 45.42 | 36.36 | 47.41 | 46.04 | 44.06 | 54.68 | 40.42 | 57.14 | 54.96 | 64.65 |

Table 2: Relative Pricing Errors

This table reports the median squared average cross-sectional relative pricing error, namely the ratio between the pricing error implied by our benchmark BMA-SBB-SBV model and the one implied by the competing restrictions. Conditional intercepts and risk exposures are sampled from their marginal posterior distribution obtained integrating out both parameter and model uncertainty. Median values of the pricing error measure are taken at each time t from the output of the MCMC estimation scheme detailed in appendix A. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors for all the models.

| Models | Sample 1999:01-2014:12 | | | | Sample 1999:01-2007:01 | | | | Sample 2007:01-2014:12 | | | |
|-------------|------------------------|-------|-------|-------|------------------------|-------|-------|-------|------------------------|-------|-------|-------|
| | Mean | Std | 5% | 95% | Mean | Std | 5% | 95% | Mean | Std | 5% | 95% |
| BMA-SBB | 0.283 | 0.201 | 0.332 | 0.273 | 0.261 | 0.070 | 0.320 | 0.211 | 0.313 | 0.189 | 0.350 | 0.276 |
| BMA-RWB-RWV | 0.417 | 0.633 | 0.415 | 0.496 | 0.385 | 0.268 | 0.410 | 0.378 | 0.458 | 0.568 | 0.415 | 0.460 |
| SBB | 0.319 | 0.205 | 0.345 | 0.298 | 0.351 | 0.528 | 0.344 | 0.377 | 0.297 | 0.218 | 0.316 | 0.268 |
| SBB-SBV | 0.478 | 0.405 | 0.484 | 0.444 | 0.492 | 0.760 | 0.484 | 0.517 | 0.468 | 0.404 | 0.435 | 0.415 |
| RWB-RWV | 0.359 | 0.227 | 0.424 | 0.334 | 0.329 | 0.076 | 0.439 | 0.278 | 0.402 | 0.211 | 0.445 | 0.331 |

Table 3: Variance Ratios

This table reports the ratio of the predictable variation explained by our benchmark model over competing models across real estate, stock and bond portfolios. The table reports the median values obtained from the marginal distribution of the risk exposures across assets. Draws from the marginal distribution are simulated from the MCMC estimation output by integrating out both parameter and model uncertainty. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors for all the models.

| | REIT | | | | | | | | | | | Bond Portfolios | | | | | |
|-------------|---------------------|--------|-------|-------|--------|-------|-------|--------|-------|---------|-------|-----------------|-------|-------|-------|------------|-------|
| | Ind | Office | Shop | Malls | FreeSt | Apts | Homes | Health | Lodg | Storage | Mortg | 10-yrs | 5-yrs | 3-yrs | 1-yrs | High-Yield | |
| BMA-SBB | 2.228 | 1.325 | 2.183 | 2.088 | 1.574 | 1.767 | 1.768 | 1.597 | 1.025 | 1.577 | 1.681 | 2.843 | 2.094 | 1.048 | 1.059 | 1.651 | |
| BMA-RWB-RWV | 1.437 | 1.129 | 1.187 | 1.268 | 1.108 | 1.244 | 1.323 | 1.127 | 1.005 | 1.191 | 1.349 | 1.913 | 1.077 | 1.248 | 1.035 | 1.565 | |
| SBB | 2.567 | 8.001 | 3.735 | 4.253 | 3.153 | 3.154 | 2.616 | 1.887 | 1.699 | 2.028 | 2.476 | 1.631 | 1.655 | 1.144 | 1.045 | 1.678 | |
| SBB-SBV | 1.934 | 2.142 | 1.661 | 1.834 | 1.538 | 1.376 | 1.549 | 1.155 | 1.221 | 1.574 | 1.287 | 1.956 | 1.769 | 1.348 | 1.035 | 1.791 | |
| RWB-RWV | 1.996 | 1.620 | 2.410 | 3.447 | 1.387 | 4.010 | 1.677 | 1.530 | 1.520 | 2.044 | 3.251 | 1.584 | 1.539 | 1.448 | 1.002 | 1.469 | |
| | | | | | | | | | | | | | | | | | |
| | Industry Portfolios | | | | | | | | | | | | | | | | |
| | Food | Mines | Oil | Clths | Durbl | Chems | Cnsum | Cnstr | Steel | FabPr | Machn | Cars | Trans | Utils | Rtail | Finan | Other |
| BMA-SBB | 1.046 | 1.014 | 1.087 | 1.003 | 1.139 | 1.163 | 2.029 | 0.992 | 0.993 | 1.047 | 0.983 | 0.998 | 1.248 | 1.749 | 1.144 | 1.023 | 1.064 |
| BMA-RWB-RWV | 1.216 | 0.984 | 1.112 | 1.004 | 1.190 | 1.139 | 1.767 | 0.987 | 1.069 | 1.037 | 0.989 | 0.962 | 1.133 | 1.521 | 1.250 | 1.032 | 1.065 |
| SBB | 1.276 | 3.413 | 2.654 | 3.800 | 4.934 | 14.44 | 1.255 | 9.025 | 2.164 | 2.374 | 1.356 | 3.965 | 2.486 | 1.675 | 3.667 | 7.259 | 2.572 |
| SBB-SBV | 0.976 | 1.512 | 1.844 | 1.518 | 1.247 | 1.681 | 1.004 | 1.160 | 1.867 | 1.316 | 1.526 | 1.498 | 1.681 | 1.108 | 1.869 | 1.848 | 2.374 |
| RWB-RWV | 1.200 | 1.910 | 2.564 | 1.557 | 1.613 | 1.974 | 1.741 | 1.243 | 2.362 | 1.965 | 1.957 | 1.660 | 2.293 | 5.577 | 2.092 | 1.631 | 1.428 |

Figure 1: REIT Indexes

The figures plot the REIT total return indexes for different underlying investment categories. Industrial and Office REITs are aggregated in a “Industrial/Office” (I&O) sector, Shopping Centers, Regional Malls, Free Standing shops REITs into a “Retail” sector, and Apartments, Manufactured Homes into a “Residential” one. As a benchmark, we also plot the total return index for the value-weighted market portfolio (black solid line). To favor comparability across different sectors, all indexes are normalized to equal 100 in correspondence to the end of January 2007. Data are monthly and cover the period 1994:01-2013:12.

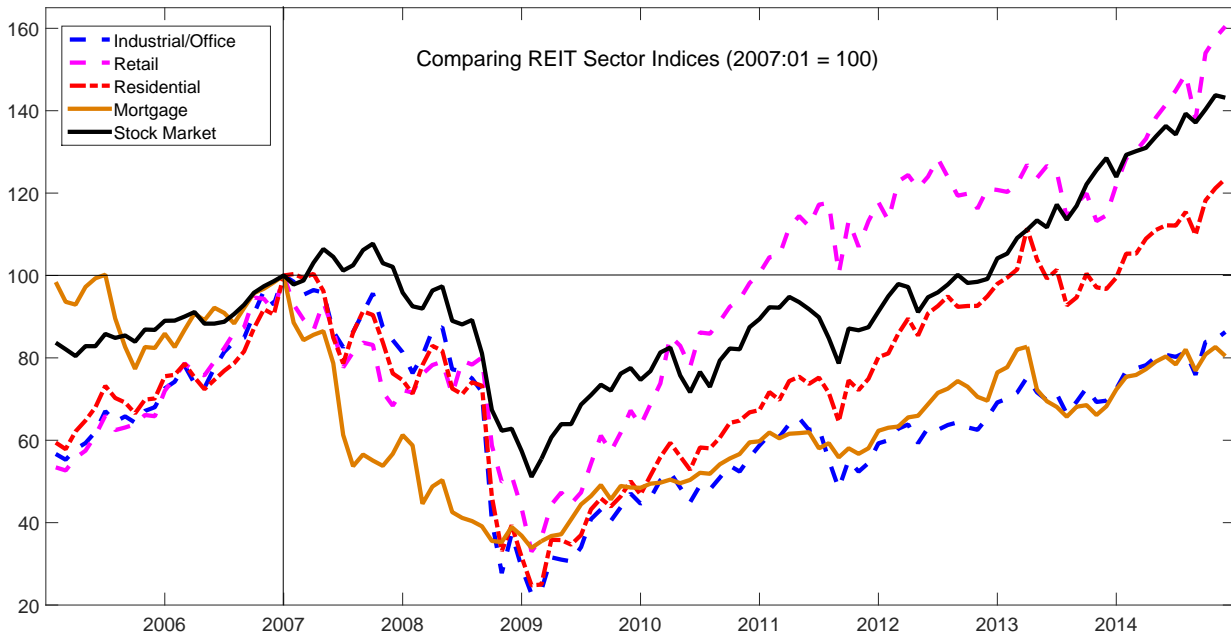
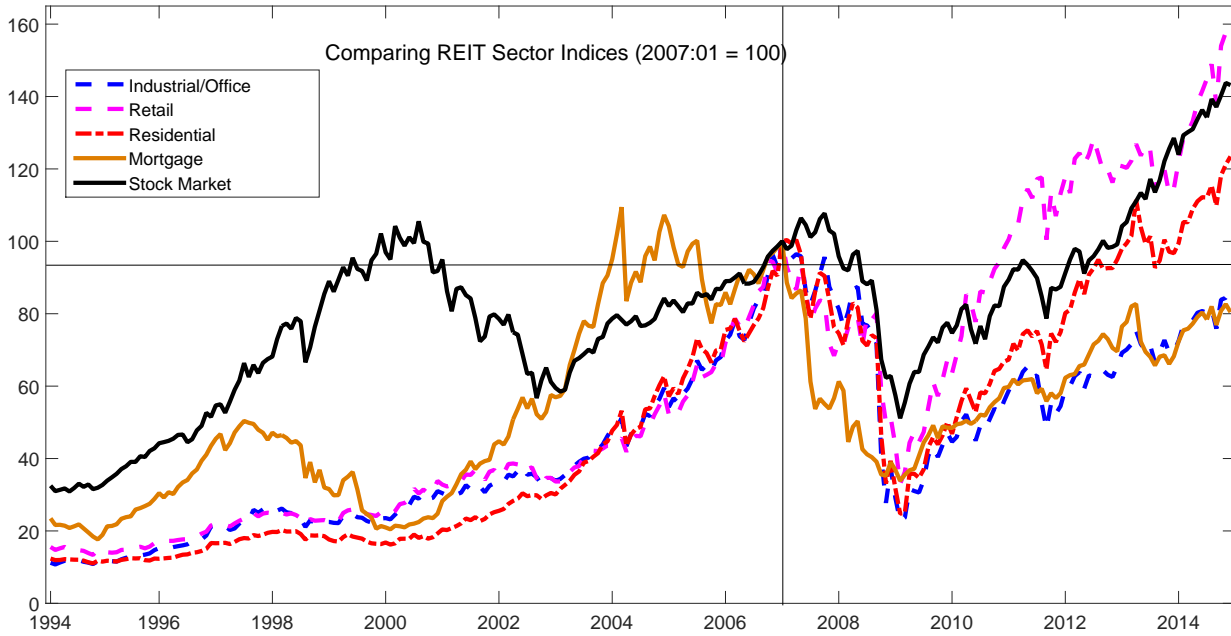


Figure 2: Time Series of Pricing Errors

The figure plots the conditional intercepts, i.e. the Jensen's alphas, across different REIT investment categories. For ease of exposition, the figure does not report Healthcare and Self-Storage REITs. Apartments and Manufactured Homes represent the "Residential" sector. Intercepts are sampled from their marginal distributions once parameter and model uncertainty have been integrated out. Marginal distributions are approximated through the MCMC estimation scheme detailed in Appendix A. The figure shows the result for our general Bayesian Model Averaging specification with Stochastic Breaks in Betas and Stochastic Breaks in Volatility (BMA-SBB-SBV). The solid blue line represents the median value of the alpha at time t and the dot dashed black lines are the 95% confidence intervals. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors.

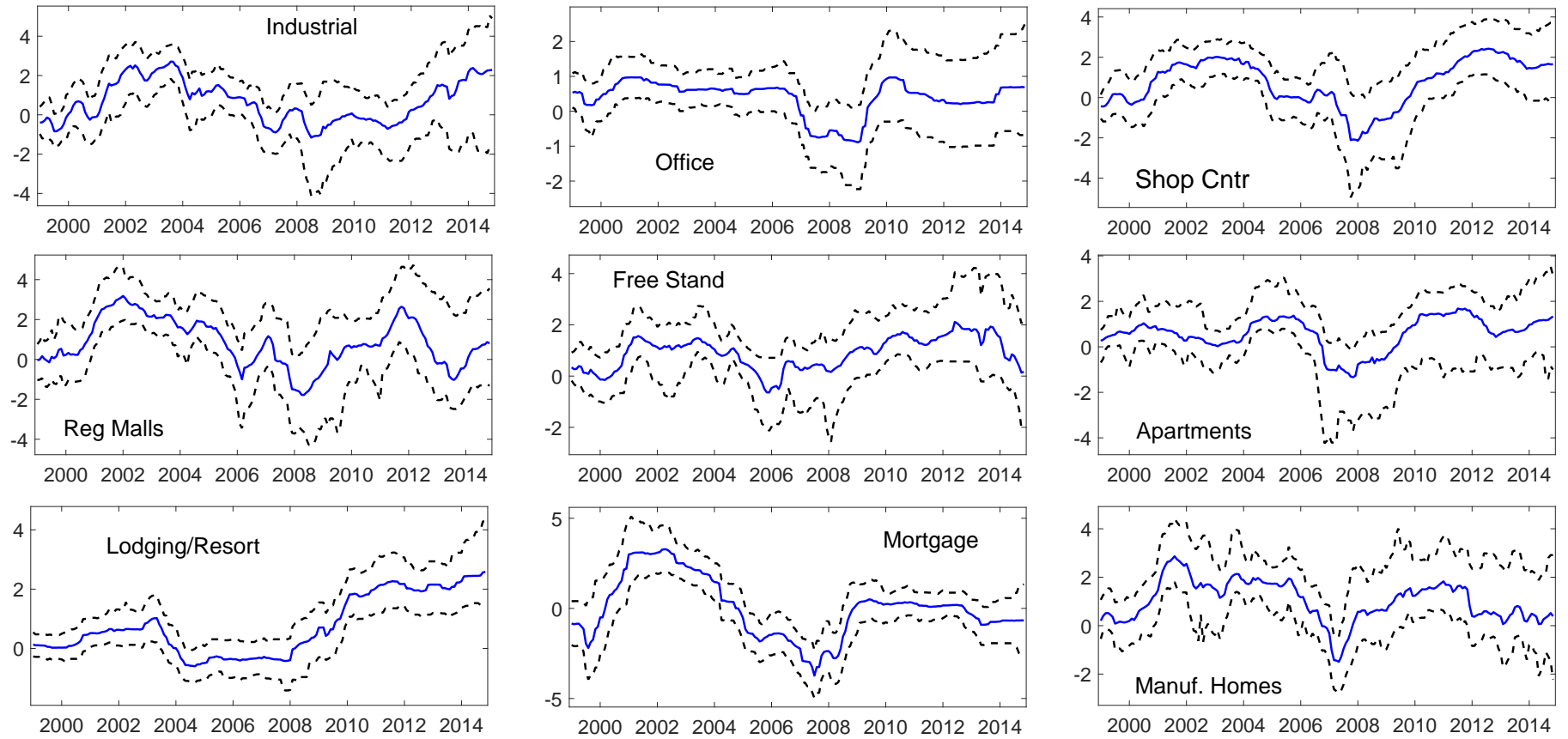


Figure 3: Marginal Probability of a Change Point in Factor Loadings

The figure reports the median estimates of the marginal posterior probability across different REIT investment categories. Break probabilities are sampled from their marginal distributions fully acknowledging uncertainty on the “right” set of risk factors. Marginal distributions are approximated through the MCMC estimation scheme detailed in Appendix A. The figure shows the result for our general Bayesian Model Averaging specification with Stochastic Breaks in Betas and Stochastic Breaks in Volatility (BMA-SBB-SBV). Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors.

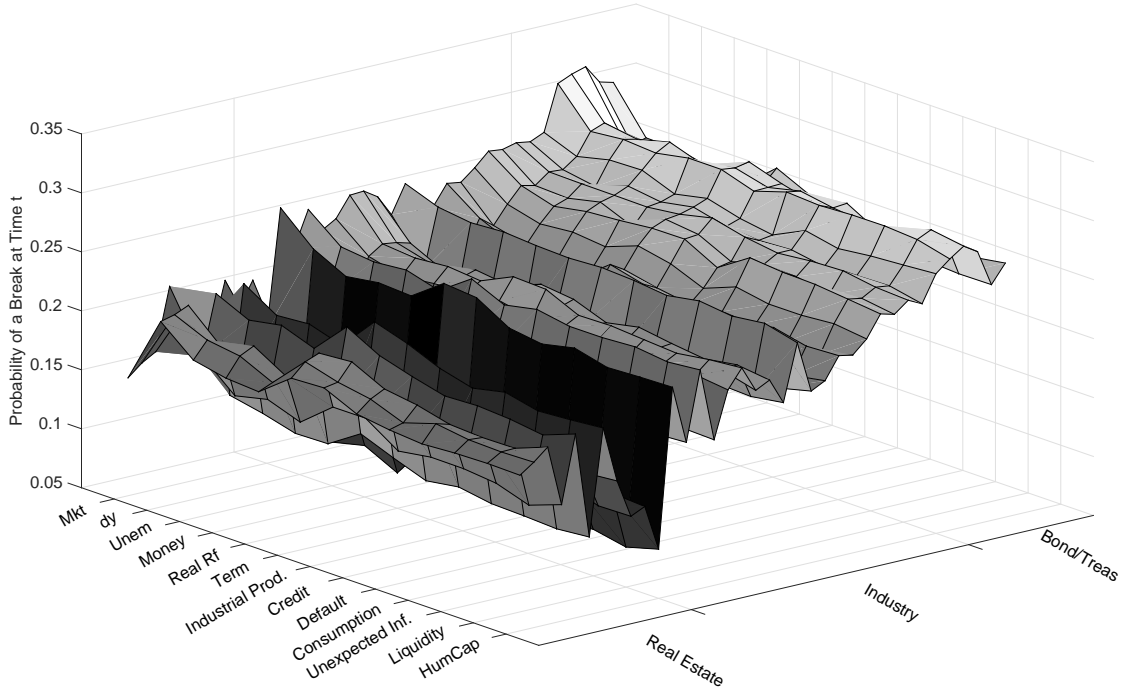


Figure 4: Posterior Probability of Inclusion of a Risk Factor

The figure reports the median estimates of the posterior probability that a certain risk factor effectively enters in the linear asset pricing model, computed across different REIT investment categories. Inclusion probabilities are sampled from their marginal distributions fully acknowledging uncertainty on both latent betas, idiosyncratic risks and their structural parameters. Marginal distributions are approximated through the MCMC estimation scheme detailed in Appendix A. The figure shows the result for our general Bayesian Model Averaging specification with Stochastic Breaks in Betas and Stochastic Breaks in Volatility (BMA-SBB-SBV). Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors.

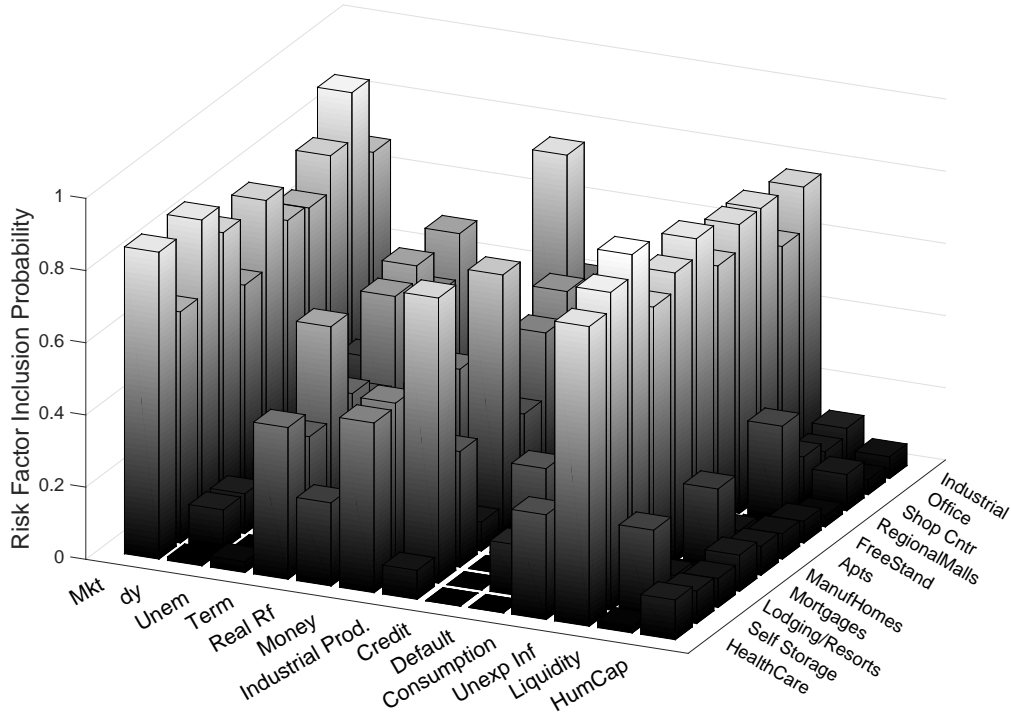


Figure 5: Exposures of REITs to Market Risk

These plots show the conditional exposures to market risk, across different REIT investment categories. Market risk is measured as the returns on the aggregate market portfolio in excess of the risk free rate. Apartments and Manufactured Homes represent the “Residential” real estate sector. Betas are sampled from their marginal distributions once parameter and model uncertainty have been integrated out. Marginal distributions are approximated through the MCMC estimation scheme detailed in the online appendix. The figure shows the result for our general Bayesian Model Averaging specification with Stochastic Breaks in Betas and Stochastic Breaks in Volatility (BMA-SBB-SBV). The solid blue line represents the median value of the alpha at time t and the dotted dashed black lines are the 95% confidence intervals. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors.

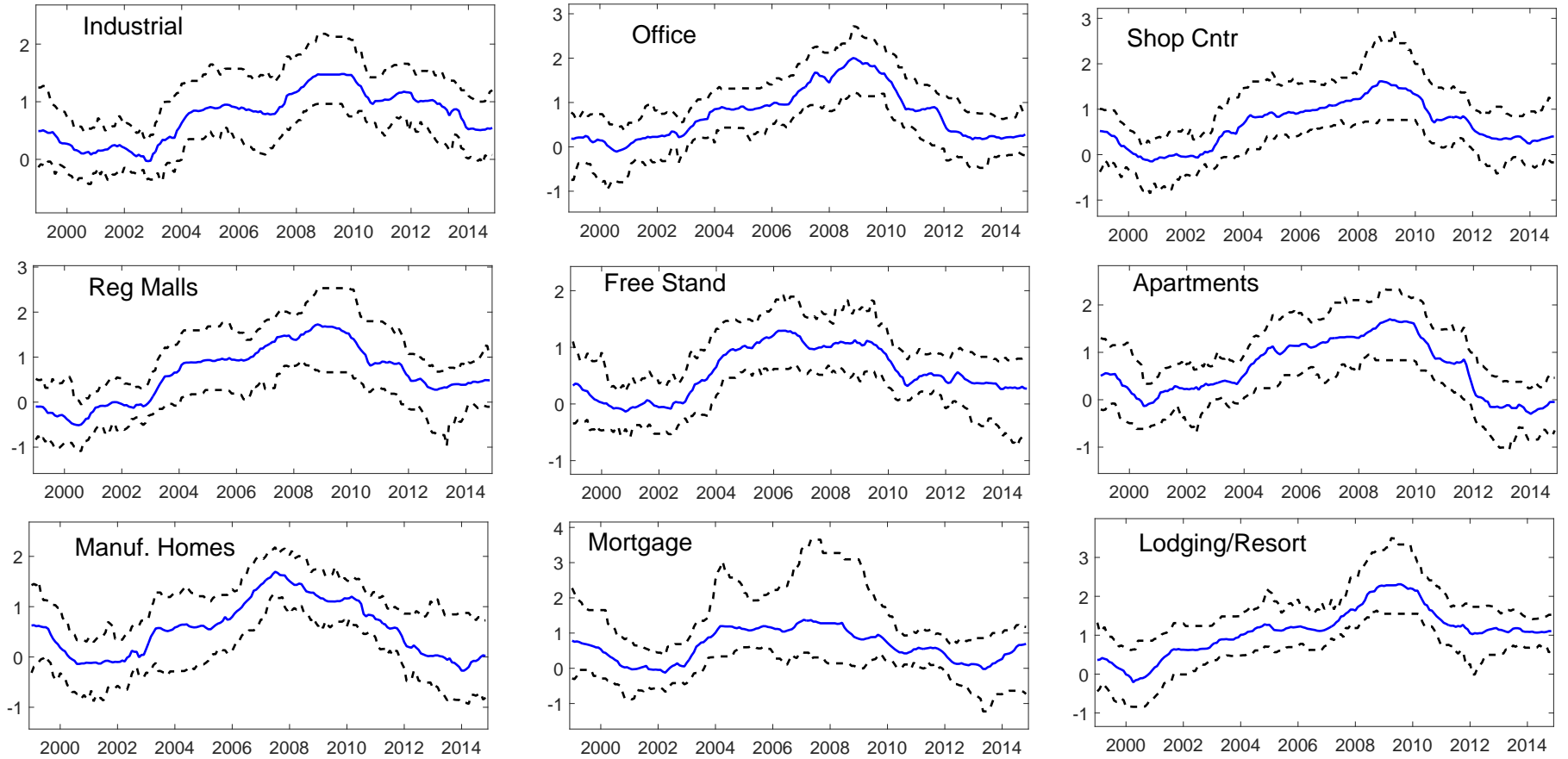


Figure 6: Exposures of REITs to Interest Rates Risk

These plots show the conditional exposures to shocks on term spread across different REIT investment categories. This spread is the difference between 10-year and a 1-year government bond yields. Apartments and Manufactured Homes represent the “Residential” real estate sector. Betas are sampled from their marginal distributions once parameter and model uncertainty have been integrated out. Marginal distributions are approximated through the MCMC estimation scheme detailed in Appendix A. The figure shows the result for our general Bayesian Model Averaging specification with Stochastic Breaks in Betas and Stochastic Breaks in Volatility (BMA-SBB-SBV). The solid blue line represents the median value of the alpha at time t and the dotted dashed black lines are the 95% confidence intervals. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors.

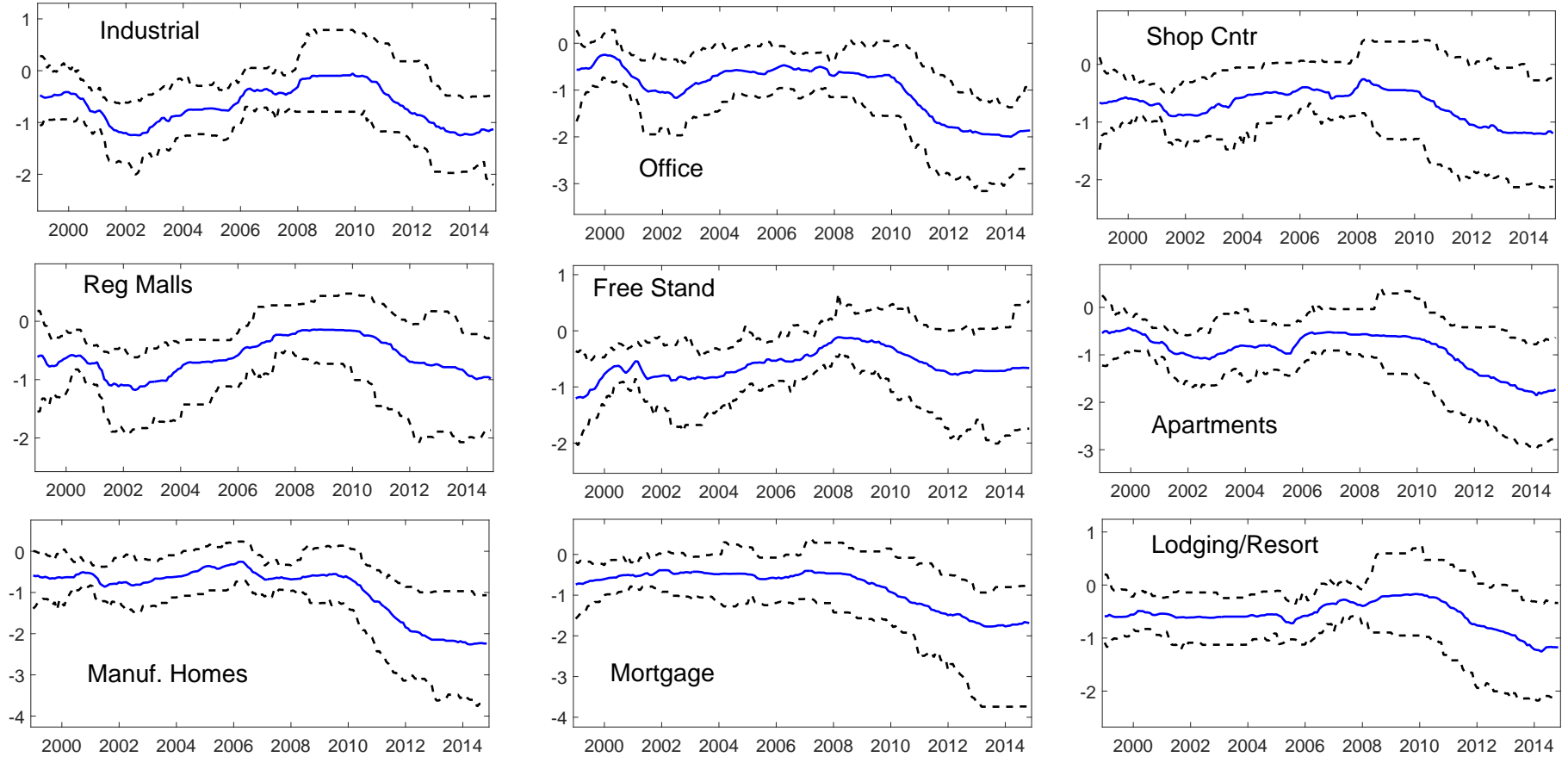


Figure 7: Exposures of REITs to Inflation Risk

These plots show the conditional exposures to shocks to unexpected inflation across different REIT investment categories. Unexpected inflation is measured as the residuals from an ARIMA(1,1,1) model fitted to the (seasonally adjusted) CPI index. Apartments and Manufactured Homes represent the “Residential” real estate sector. Betas are sampled from their marginal distributions once parameter and model uncertainty have been integrated out. Marginal distributions are approximated through the MCMC estimation scheme detailed in Appendix A. The figure shows the result for our general Bayesian Model Averaging specification with Stochastic Breaks in Betas and Stochastic Breaks in Volatility (BMA-SBB-SBV). The solid blue line represents the median value of the alpha at time t and the dotted dashed black lines are the 95% confidence intervals. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors.

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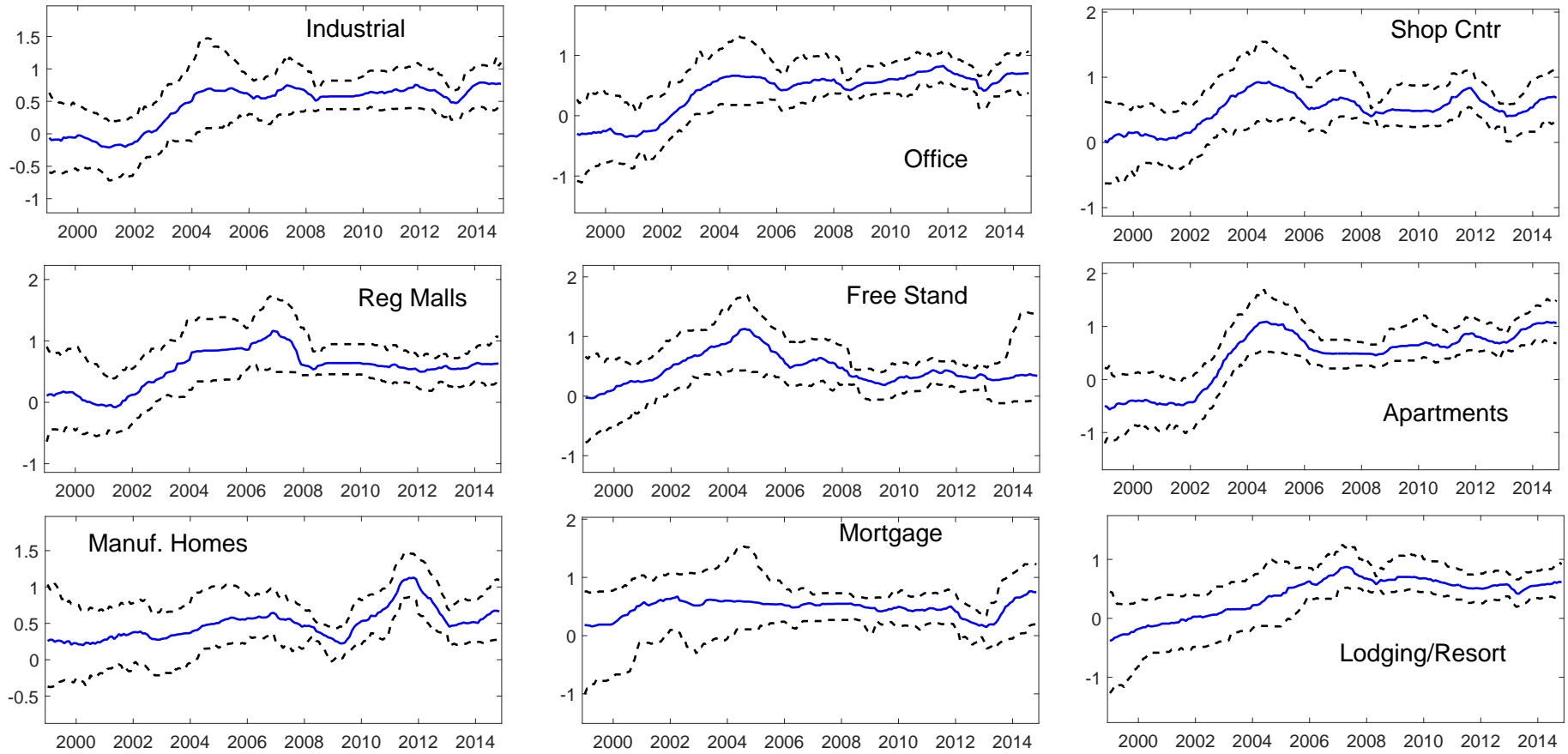


Figure 8: Dynamics of Idiosyncratic Risk

These plots show the dynamics of idiosyncratic risk across different REIT investment categories. Apartments and Manufactured Homes represent the “Residential” real estate sector. Idiosyncratic risks are sampled from their marginal distributions once parameter and model uncertainty have been integrated out. Marginal distributions are approximated through the MCMC estimation scheme detailed in Appendix A. The figure shows the results for our general Bayesian Model Averaging specification with Stochastic Breaks in Betas and Stochastic Breaks in Volatility (BMA-SBB-SBV). The solid blue line represents the median value of the alpha at time t and the dotted dashed black lines are the 95% confidence intervals. Data are monthly and cover the sample period 1994:01 - 2014:12. The first five years of monthly data are used to calibrate the priors.

